Whiskers - How Robots Can Learn from Rats

Dissertation

zur

Erlangung der naturwissenschaftlichen Doktorwürde

(Dr. sc. nat.)

vorgelegt der

Mathematisch-naturwissenschaftlichen Fakultät

der

Universität Zürich

von

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aus

Deutschland

Promotionskomitee

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Zürich, 2006

The following paper was accepted as a dissertation by the University of Zurich, Faculty of Science in the winter term 2006/2007.

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Abstract

Autonomous agents have to rely on their senses to behave adaptively in the real world. Tactile sensing can provide detailed and rich information on the immediate surroundings and is particularly valuable under conditions where vision fails. While humans do most of their tactile exploration with the highly sensitive fingertips, a wide range of animals has developed a sophisticated somatosensory organ for the same purpose, the whisker pad. It has been shown that the resolution of rats discriminating textures with their whiskers rivals that of primate fingertips. This amazing sensory power inspired us to build a mobile robot with an artificial whisker system which is presented in this thesis. Building a physical robot, we apply the synthetic methodology which has several important implications. One of the most important is that the robot has to move in the real world and therefore faces the same constraints as natural agents. Unlike in simulation, a physical agent is automatically subject to the physical laws and to noise, which are both hard to simulate with enough precision. Moreover, with the biologically inspired robot model, we can explore questions not readily available in animal experiments.

At the same time, the synthetic methodology uncovers important issues which are taken for granted if only the final product of an evolutionary process, the animal, is considered. One example is the importance of sensory morphology for different behaviors. We investigate the relationship between task environment and whisker morphology as well as with different levels of adaptivity. Furthermore, the tactile power of this sensor is assessed by taking sensorimotor interactions into account. Active sensing is exploited to increase the discriminatory capacity of the whiskers, as well as a redundant array consisting of a rich variety of individual sensory hairs. Finally we present tactile behavior and discuss the conclusions drawn from our experiments with a real-world biorobotic model.

Zusammenfassung

Um sich in der realen Welt adaptiv zu verhalten, müssen autonome Agenten über eigene sensorische Systeme verfügen. Der Tastsinn zum Beispiel liefert auch dann noch detaillierte und vielfältige Informationen über die nächste Umgebung, wenn das visuelle System versagt. Menschen verwenden hauptsächlich die Fingerspitzen für exploratives Tasten, während eine Vielfalt von Tieren dafür ein ausgefeiltes somatosenorisches Organ entwickelt hat, nämlich die Schnurrbarthaare. Es konnte gezeigt werden, dass Ratten mit ihren Schnurrbarthaaren die Rauigkeit von Texturen etwa gleich gut auflösen können, wie Primaten das mit ihren Fingerspitzen können. Diese eindrückliche sensorische Leistung hat uns inspiriert, einen beweglichen Roboter mit künstlichen Schnurrbarthaaren zu bauen, der der vorliegenden Arbeit zugrunde liegt. Indem wir einen physischen Roboter bauen, wenden wir die synthetische Methode an. Das hat bedeutende Auswirkungen: Eine der wichtigsten ist, dass der Roboter sich in der realen Welt bewegen muss und damit automatisch auch den gleichen Beschränkungen unterworfen ist, wie die natürlichen Agenten. Anders als in einer Simulation ist der Agent automatisch den physikalischen Gesetzen und Rauschen in den Sensoren ausgesetzt. Beides ist aufwändig zu simulieren. Ausserdem können wir mit dem biologisch-inspirierten Roboter Dinge untersuchen, die im Tierexperiment nicht angegangen werden können.

Die synthetische Methode zeigt spannende Fragen auf, deren Lösung für selbstverständlich genommen wird, wenn nur das Endprodukt der Evolution, nämlich das fertige Tier, betrachtet wird. Ein Beispiel für solch eine Frage ist die Bedeutung der Sensormorphologie für unterschiedliche Verhaltensweisen. Wir untersuchen die wechselseitige Abhängigkeit zwischen der Morphologie der Schnurrbarthaare und den spezifischen Charakteristika verschiedener Aufgaben. Ausserdem betrachten wir unterschiedliche Ausprägungen von Adaptivität. In einem weiteren Schritt loten wir das Potential für taktile Wahrnehmung aus, wobei wir insbesondere die Bedeutung der sensomotorischen Interaktionen berücksichtigen. Aktive Wahrnehmung kann dazu ausgenutzt werden, die Unterscheidungsfähigkeit der Schnurrbarthaare zu erhöhen.

Dazu tragen auch eine reiche Auswahl an individuellen sensorischen Haaren bei, die in einem redundanten Schnurrbarthaar-Array kombiniert sind. Abschliessend präsentieren wir taktiles Verhalten und diskutieren Schlussfolgerungen, die wir aus der Untersuchung dieses für die reale Welt konstruierten Bioroboter ziehen.

Acknowledgments

Working at the Artificial Intelligence Lab provided me with a stimulating and diverse environment: First of all, I would like to thank my supervisor, Rolf Pfeifer, for the opportunity and the freedom to develop and explore my own scientific interests and ideas. Special thanks go to my co-supervisor Andreas Engel for his thoughtful and constructive comments during the writing of this thesis. Invaluable input were the discussions at various AMouse meetings, and I want to acknowledge the project members: Peter König, Mathew Diamond, Ralf Möller, Gerhard Engler, Christiane Vahle-Hinz, Konrad Körding, Jörg Hipp, Ehsan Arabzadeh, Moritz von Heimendahl and DaeEun Kim.

During the course of the project, I received enormous support from Hiroshi Yokoi, Max Lungarella, Martin Krafft and numerous other people at the AI lab. I would like to specifically thank the two people who have shared an office with me: Peter Eggenberger-Hotz and Simon Bovet. Long, spontaneous discussions on our work, moral support as well as a lot of fun made my days! I also thank all the other present and former lab members that I have not mentioned so far (in random order and probably not complete): Hanspeter Kunz, Verena Hafner, Lukas Lichtensteiger, Fumiya Iida, Josh Bongard, Chandana Paul, David Andel, Gabriel Gomez, Nathan Labhart, Maik Hadorn, Marc Ziegler, Shuhei Miyashita, Raja Dravid, Thomas Netter, Luis Correira and Jan Wantia.

I cannot sufficiently express how much my family has helped me. Without the continuous and unconditional support of my parents, Ida and Helmut Fend, my sister Ruth and - last but not least - Christian, this thesis would not be finished now.

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Chapter 1

Introduction

1.1 Motivation: A Strange Perceptual World

The diversity of shapes, colors, sizes, and behaviors that can be found in animals is a ceaseless source of marvel. As varied as their appearance are the environments animals live in, and therefore the requirements on their sensory and motor abilities. Perception of the world strongly depends on the one hand on the specific characteristics and the range of their senses and on the other hand on the animals' abilities to move. Animals rely on a large variety of different sensory channels, and they move in different environments as well as at different speeds and altitudes generating perceptual experiences which can differ a lot from human perception.

One example of a sensory system lacking in humans are whiskers - prominent in the face of rats or cats for example. Usually, we do not expect sophisticated sensory capabilities in just a bunch of hair - but we are wrong. These hairs are refined tactile organs. Some animals use them heavily for haptic perception as well as in social interactions - much as we use our fingertips. Exploring this strange perceptual world by building a robot with artificial whiskers, i.e. by applying the synthetic methodology to study how morphology and material properties may influence the behavior of the robot as well as how surface textures can be discriminated is the purpose this thesis.

1.2 The Synthetic Methodology: Understanding by Building

There is a fundamental difference in the analytical approach of most "classical" scientific disciplines (e.g. neuroscience, psychology, physics) and the synthetic approach of

modern artificial intelligence research. For example, in neuroscientific research, scientists study immensely complex systems which have evolved to adaptively function in a dangerous and changing environment. To understand how this can be achieved, the complete agent - the animal - is broken down into subsystems such as single neurons which can be studied in controlled setups on specific questions. For example, to understand the brain, powerful methods have been developed to study the functioning of single neurons or molecules. Much has been learned about specific ion channels, synapses and single neurons, but so far it is not clear how the complete agent, i.e. the animal, and its behavior can be reconstructed from the these components.

In behavior-oriented approaches to neuroscience, the whole animal is studied by removing specific parts, e.g. lesioning brain areas or knocking out specific genes, and specific loss of or change in function is assessed in the animal. Again, important functionalities have been identified using this approach - but often the interactions between the remaining parts and the redundancy of biological designs compensate for the removed parts. Therefore, it is difficult to identify all functions of a given brain area or gene. Needless to say, there are immense amounts of possible interactions to be studied, and it seems impossible to cover all.

The synthetic methodology applied in this thesis takes a different approach. Instead of analytically decomposing a specific biological system, we strive to understand behavior and perception by building a robotic model. The conceptual foundations of this bottom-up approach have been discussed in detail in [123–125]. Interestingly, recent efforts in biology named *synthetic biology* also aim at assembling life-like structures from chemical building blocks (for review see [13]).

1.3 From Classical Artificial Intelligence to Embodied Artificial Intelligence

When the field of Artificial Intelligence was founded at the Dartmouth Conference in 1956, the prime focus was to develop "thinking machines", meaning machines capable of high-level human cognition such as planning, theorem proving, or playing chess. But to be able to function in the real world, other abilities are crucial: an agent has to be able to find food, avoid being eaten, and to find a mate for reproduction. Locomotion and perception are much more vital than being able to play chess or proving theorems - and they seem much harder to achieve for an artificial system.

Much of early artificial intelligence focused on the manipulation of symbols, ab-

stract notions of categories implemented by a computer program. Once symbols have been defined, computers are very good at manipulating them, e.g. by generating complex proofs or by manipulating symbols of objects in a world model. While classical artificial intelligence was quite successful at solving problems we usually consider to be very difficult, such as logical inferences or playing chess, it has more or less failed to solve seemingly easy tasks such as interpreting natural scenes.

Unfortunately for this approach, an artificial system has to generate the symbols from unstructured, messy and noisy data when interacting with the real world via sensors and motors. There are no labels telling the computer program whether for example, there is a chair or a table in a visual scene. Perception - making sense out of a noisy, unlabeled stream of sensory data - has turned out to be one of the hardest problems in intelligence research.

In the 1980's, a new paradigm in artificial intelligence emerged focusing on system-environment interactions. This approach was soon termed *embodied artificial intelligence* as it proposes that no system - natural or artificial - can behave intelligently in the real world without a body [23, 125]. "Intelligence needs a body" encompasses the notion that an agent needs to be able to move as well as sense. The interaction between the agent and its environment creates rich and diverse sensation. Being able to actively influence the stimulation of the agent's senses can generate structured sensory input correlated to the agent's own activity.

If having a body is crucial for intelligence to arise, it is not surprising that the morphology of this body is also very influential. Recently, this notion has been extended and several researchers have investigated the large role of specific morphologies for various behaviors. Two main questions have been pursued, firstly, how can a body be designed to allow for energy efficient, natural and stable locomotion with minimal control [29, 74, 75, 101, 119], and second, how can sensory morphologies e.g. of an insect eye be adapted and optimized for a specific sensory task [95, 96], and how do these morphologies influence learning [96].

1.3.1 Biorobotics

Embodied artificial intelligence has often studied biological examples both for inspiration as well as in order to contribute to problems difficult to study in biological research. While classical artificial intelligence was mostly interested in behaviors or tasks specific of humans, biorobotics is more generally interested in understanding and modeling natural intelligence commonly found in animals. Animals which are

often highly optimized for their specific ecological niche has inspired engineers. To understand the contribution of these adaptations, modeling usually involves building a physical robot and not pure simulation.

The reasons for studying animal intelligence are manifold: On the one hand, the variety of different ecological niches has led to the evolution of many highly specialized and efficient solutions to common problems e.g. in the area of perception. Studying lower levels of intelligence than the human being's also offers greater chances of success: if we are able to understand simple systems already capable of complex and adaptive behavior, we might be able to increment and generalize to more human-level intelligence.

Especially well studied are complex behaviors in insects such as the desert ant *Cataglyphis*. Its navigation strategies have been investigated both by biologists (see for example [154]) and by roboticists [92]. In their experiments, Lambrinos et al. developed a custom robot, the Sahabot series, and performed navigation experiments in the native environment of the desert ant, namely the Tunisian desert. They investigated whether the robot was able to navigate back to its nest using models derived from animal experiments.

The neural structures of insects contain only a fraction of the neurons found in mammalian brains. Some neuronal networks functionally linked with specific behaviors have been studied in extensively and have thus been accessible for detailed modeling on a robotic platform (for review see [152]). An example of careful modeling of a biological behavior with its underlying neural circuits is cricket phonotaxis. Male crickets are attracted by the sound of female crickets and are able to approach the female even from large distances. Barbara Webb has studied this behavior by building a robot equipped with similar perceptual capacity in the auditory system as the cricket (see for example [72, 151]), and she has tested neural architectures closely modeled on what is known from the cricket [134, 153].

Compared to insect brains, mammalian brains are much more complex. A particularly well-studied mammalian system is the rat brain. Many brain areas found in the human brain are already present in the rat, even though smaller and of lower complexity. Some biorobotics experiments have been conducted on rat navigation and the learning of place cells in the hippocampus (see for example [58]).

In this thesis, we present a different type of biorobotics model. Following a bottom-up approach, we study how the morphology of whiskers is linked to behavioral tasks, and we present a series of experiments exploring the perceptual potential of biologically inspired, active whiskers which are originally introduced in this work. Since this

thesis has been conducted within the framework of the European project AMouse (artificial mouse), the robot is often called "AMouse".

1.4 Original Contributions

This thesis is focused on a specific sensory modality, namely haptic sensing using artificial whiskers on a robot. The experiments presented in the following chapters contribute mainly to two fundamental questions. First, we study in detail the contribution of whisker sensory morphology to basic locomotion tasks. Second, a new tactile sensory modality and some of its possible applications are presented. Specifically:

- A main contribution of this thesis has been the design of a robot with active artificial whiskers and an omnidirectional camera. This robot has - in its evolving designs - been used throughout this thesis, and it has been used by other researchers as well. As whiskers are important and highly optimized sensors in a variety of animals, biological knowledge has been incorporated into the design of this sensor while at the same time, simplifying certain aspects. We have shown that basic properties of the sensory hair are preserved, and that they can be measured using a capacitor microphone as the basic sensory unit (chapter 3).

- Several experiments and results explore the role of whisker morphology for performance of the agent on two different tasks. We introduce the concept of the physical space an agent takes up in contrast to the sensory space which it can perceive. Robot experiments and artificial evolution in a physically realistic simulation[1] have shown that a reflex-driven agent is only able to move through all of its environment if the physical and the sensory space of the agent are well balanced (chapters 4, 5, and 6).

- By including a different behavioral task, namely wall following, we have shown that the whisker morphology performs best which closely resembles the whisker morphology commonly found in animals. We hypothesize that wall following is a behavior where animals are more dependent on whiskers than obstacle avoidance (chapter 6).

- In a second series of experiments, we have studied tactile perception based on artificial whiskers. Using unsupervised learning of real-world whisker data, we

[1]The ODE simulations described as part of chapter 6 were programmed by Simon Bovet.

find spectrotemporal receptive fields where most simulated neurons respond to activity which is localized in frequency space and time (chapter 7).

- We show that by structuring sensory data acquired actively by taking the motor signals into account, we can significantly enhance texture discrimination abilities (chapter 8).

- Using a mobile robot, we perform texture discrimination experiments. By including a basic reflex to position the robot, textures can be discriminated (chapter 9).

1.4.1 Overview

This thesis is organized around 6 papers, all of them peer-reviewed and published in the proceedings of relevant conferences and in scientific journals. In the following chapter, we will provide background on biological knowledge of the whiskers system as it is relevant to this thesis. Some of this is also discussed in the individual papers which constitute this thesis, but not as comprehensive. We will also discuss other technical realizations and experiments on artificial whiskers in section 2.2. It is worth noting that after the publication of the first papers presented in this thesis, more projects started to develop and use biologically inspired whisker sensors.

Chapter 3 describes the technical realization of the artificial whisker sensor and the construction of the robot employed in this thesis as well as first experiments characterizing material properties of the sensor. Chapters 4, 5 and 6 investigate the contribution of whisker morphology to different behavioral tasks on a robot. The experiments deal with two different tasks, and they include learning and artificial evolution in simulation. The second main strand of research presented in this thesis explores texture discrimination with artificial whiskers.

In chapter 7, we describe and analyze unsupervised learning of somatosensory receptive fields using sparse coding. Chapter 8 describes the dependence of texture discrimination on active whisking, while the focus of chapter 9 is on discriminating textures on a mobile robot.

In chapter 10, the main results are summarized and their implications for robotics and biology are discussed. Finally, possible future research topics are presented.

Chapter 2

Whiskers in Biology and Robotics

Sensory systems and perception are crucial for survival in a complex and changing world. In nature, many different solutions for tactile sensing can be found. We as humans use pressure sensors embedded in the skin that get activated whenever we touch something. Especially sensitive are the tongue, the lips and the fingertips. We can also sense motion on hairs, but rarely use it. Several different animal species have evolved a tactile sensing organ relying on hair as a transduction mechanism. Such hairs are commonly called whiskers. The whiskers do not replace tactile sensing with pressure sensors in the skin, but rather complement it. A big advantage of the sensory hairs is that they extend the range of tactile sensing beyond the surface of the physical body.

To build an artificial model of a whisker sensor to study its perceptual power, we collect inspiration and knowledge from biology. In the following section, we will give an overview on whiskers in different animals with a focus on their contribution to behavior. Finally, we will discuss approaches to artificial whiskers and their application in robotics.

2.1 Biological Background on Whiskers and Antennae

The first class of animals that comes to mind when we speak about whiskers, are the rodents. Prominent representatives of rodents are rats, mice, guinea pigs, hamsters, chinchilla and many more. Rodents are known for their well-developed whisker pad [21] which has been most closely studied in rats. But whiskers can be found in many more species.

(a) (b)

Figure 2-1: Examples of whisker bearing animals. (a) Photograph of a cat. (b) Photograph of a rat (*Ratus norvegicus*).

Recently, pinnipeds such as seals, sea lions and walruses have attracted attention on their whiskers. Dehnhardt et al. showed that seals cannot only discriminate different objects by their size, but they also follow small water currents only using their whiskers [35, 36]. For a long time researches assumed that seals hunted in water using visual cues. But in the wild, blind seals were found that were well-fed and obviously able to hunt. In behavioral experiments with seals in a swimming pool, they were able to follow the turbulences in water induced by a small electrical boat. These fluctuations approximated currents generated by fish of the size of a herring. Amazingly, wild seals reliably hunt even in large waves and surge. Walruses search for food by digging in the sea floor. Doing so, they stir up sand and other floatable particles rendering the water turbid. Under these unfavorable conditions for the visual sense, they are suspected to employ their vibrissae to discriminate food objects (such as mussles) from non-food ground objects (Kastelein and van Gaalen in [128]).

The Australian water rat *Hydromys chrysogaster* has been studied as a living link between the domains of tactile sensing in water and in air. This semiaquatic mammal hunts fish, crustaceans and molluscs and shows several morphological adaptations to its wet environment. During diving, the water rat closes its eyes, relying solely on vibrissal tactile information for foraging [34]. Dehnhardt et al have also studied the anatomy of the whiskers both externally and on the follicle level and were able to show structural adaptations in terms of stiffness of the whiskers and size of the follicle linking aquatic whisker bearing animals such as seals and terrestic animal such as rats (e.g. *Rattus norvegicus*).

Another very specialized type of rodent which heavily relies on whiskers is the naked mole-rat (*Heterocephalus glaber*). This African animal spends its entire life underground in extensive networks of tunnels (Brett, 1991 in [33]). The naked mole-rat shows several adaptations to living underground, among them reduced visual function with small eyes [66] and a massively enlarged somatosensory cortex [28]. While it has no fur anymore, it has whisker-like hairs on their entire body. These hairs are regularly spaced in five rows on each side of the body and complement the well-developed whisker pad on the animal's snout. Experiments have shown that stimulation of the body hairs induces a very reliable turning behavior towards the stimulation. The angle of turning increases the further caudal the stimulated hair is located [33].

Behavioral Importance of Whiskers

Studies on animals in the wild are more difficult and often less clear-cut than laboratory experiments. Still there are studies which describe the use of whiskers in natural behavior (for review see [5]). An important behavior is the acquisition of food. Several animal species have been tested with whiskers and after removal (e.g. clipping) of whiskers. In grass-hopper mice, the time required for catching and pinning the cricket with the forepaws was increased in mice without whiskers. Similarly, some evidence indicates that whiskers play an important role in mouse killing in laboratory rats and cats, especially in completing the attack by biting [5]. After whisker removal, more attacks are needed to actually kill the prey.

Several mice strains and species have been tested on their swimmming abilities with and without whiskers [5]. Survival on submersion tests showed differences between mice with and without whiskers. In the cotton rat, it has been observed that the rats were unable to maintain their body position in and their nose out of the water without the vibrissae [4]. If all whiskers are trimmed on one side only, rats predominantely explore their environment with the remaining whiskers, i.e. they exhibit a biased wall-following behavior, both in water and on land. In water, the swimming abilities are impaired, even with one whisker array left intact [103].

Whiskers also appear to play a role in social interactions. It has been suggested that the facial muscles responsible for facial expressions work on the whiskers. Similarities between facial expressions in walruses and New Zealand fur seals have been revealed [5]. In the context of stereotyped foot-shock induced aggression, the rate of fighting was reduced after vibrissa removal. In some laboratory mice strains, the whiskers of the losers of dominance fights were trimmed.

2.1.1 Active Sensing with Whiskers

Several rodents use whiskers actively - meaning that they periodically sweep their whiskers across objects or surfaces for exploration. Such tactile behavior is not reported for cats, although they can adjust the position of their whiskers to a large extent(unpublished observation). In rats, active motion of the whiskers has been studied intensely [14, 27, 115, 135, 156]. Rats sweep their whiskers in periodic motion at $\approx 5 - 15Hz$. This motion is achieved by the combination of two types of muscles, *intrinsic* sling muscles and *extrinsic* muscles which have their anchor point outside the whisker pad [39]. While the intrinsic muscles allow for individual control of single whiskers, the extrinsic musculature deforms the whole whisker pad thereby generates a synchronous motion.

In their seminal paper on texture discrimination in blind-folded rats, Carvell and Simons have conducted video analyses of the movement of single whiskers [26]. They find that rats performing texture discrimination have a dominant whisking frequency around 8 Hz. Most of the time, several whiskers touched the discriminandum simultaneously, even though they had to trim all the whiskers except one row. Well-trained animals mostly whisked only one of the two discriminanda at a time and switched between the two before chosing the one they had been trained for. Active motion of the whiskers was complemented by head movements. Carvell and Simons also measured the average distance of contact amounting to 15 mm and the surface distance swept by a whisker, namely ≈ 9 mm. Upon contact, the amplitude of whisking decreased, suggesting that large amplitude sweeps also serve the purpose of searching. Follow-up experiments by Carvell and Simons indicate that the pattern of whisking correlates with the behavioral performance of a rat discriminating different gratings. They found that better performing rats also whisk at lower frequencies ($2 - 6Hz$) whereas the whisking power spectrum of bad performers contained high frequency components ($18 - 27Hz$) [27].

While the evidence for different whisking speeds and strategies reported previously already suggests that whisking can be controlled voluntarily, Gao et al. [52] corroborate this notion by showing that rat whisking can be controlled by an operant reinforcement scheme. Further studies have investigated the degree of control the rat has on parameters of whisking. Berg and Kleinfeld showed that the rat use active muscular control over both protraction and retraction [15]. While most of the time, rats move their whiskers synchronously both within the pad and across both whisker pads [51], it has been shown that rats can move two whiskers independently [135]. The divergence of adjacent whiskers may include motion in opposite directions,

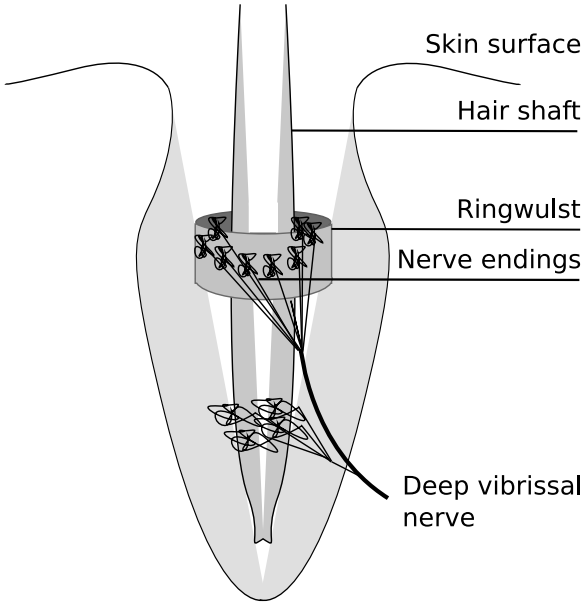


Figure 2-2: Schematic representation of a whisker follicle. Adapted from [40].

prolonged contact of one whisker with an object while the adjacent whisker continues sweeping, and one whisker resting while the other sweeps. Such tight control is probably accomplished by the intrinsic musculature of the whisker pad. It stresses the eminent role of active acquisisition of sensory data. In this study, the rat's head was fixed to isolate the effect of moving the whiskers by themselves. In freely moving agents, motion of head, body, and whiskers contribute to sensorymotor coordinated behavior.

2.1.2 Anatomy of the Whisker Follicle

To gain a basic understanding of sensory function it is often instructive to know the morphology and basic workings of the sensor. The anatomy of the whisker and the whisker follicle has also been studied in detail [40, 129, 144]. First of all, a whisker is a type of hair, chemically similar to other types of hair such as human head hair. It differs mainly in its shape: whiskers have a strong conical shape [63] and can be modeled as a conical cantilever beam. Simulations have shown that this shape renders a whisker stiff at the root while preserving flexibility at the tip [162].

While the whisker outside the skin is dead material, it originates - like all hair - from a follicle in the skin (figure 2-2 shows a schematic drawing of the follicle). Unlike ordinary hair, the whisker is surrounded by a blood-filled sinus, whose upper half has an open lumen, the Ringwulst [78]. Due to this specialized feature, the whole structure

containing follicle, sinus and whisker root is usually called the follicle-sinus complex. Functions of this blood-filled sinus could include ensuring stable temperatures at the nerve endings, damping of the whisker hair, and potentially adjusting the stiffness of the whisker follicle thereby influencing the whisker motions within the follicle. Furthermore, the whisker is surrounded by nerve endings of different types of pressure sensors, sensory endings are also found at the base of the whisker.

The number of nerve endings varies between different species, especially between terrestrial and aquatic animals. In seals (*Phoca hispida*), the number of each of the different types of nerve endings is about ten times higher than in rat and cat [34]. The same holds true for the number of nerve fibres that pass through the main nerve leaving the follicle, the deep vibrissal nerve.

Receptor Neurons and their Physiological Properties

Merkel, lanceolate and free nerve endings are the most common sensory receptors innervating the follicle-sinus complex [40, 78]. There are species-related differences in the anatomical distribution and localization of the receptors as studied for example by comparing rats and cats [40]. While these two animals have similar follicle-sinus complexes, they show different behavioral patterns in their use of the whiskers, e.g. rats actively whisk while cats do not.

Mechanoreceptors can be classified by their physiological response properties into slowly adapting type I and II vs. rapidly adapting cells. These physiological properties have been measured in skin receptors by applying pressure on the skin, first by pressing a stimulator into the skin at constant speed, and second by applying constant pressure without moving the stimulator [165]. Under the condition of constant speed, both slowly and rapidly adapting sensors respond. If constant pressure is applied, the rapidly adapting sensors quickly stop firing while the slowly adapting cells continue to signal the received pressure. Lanceolate endings are rapidly adapting [111]. Conveyed to the situation of a whisker sensor, rapidly adapting fibres only respond when a whisker is moving, while slowly adapting fibres respond both to motion and to constant deflection of the whisker (for a schematic illustration see figure 2-3).

One of the best studied slowly adapting mechanoreceptors is the Merkel cell (for review see [61]). Merkel cells are among the most numerous receptors in the whisker follicle: in cat preparations, more than 3000 have been counted even for a small follicle [55]. Recordings from type 1 nerve fibres connected to Merkel cells in cat vibrissal follicles show that the nerve fibre is able to follow a vibratory stimulus in a 1:1 manner between 80 and 1200 Hz. Below 80 Hz, the nerve fibre shows multiple discharges

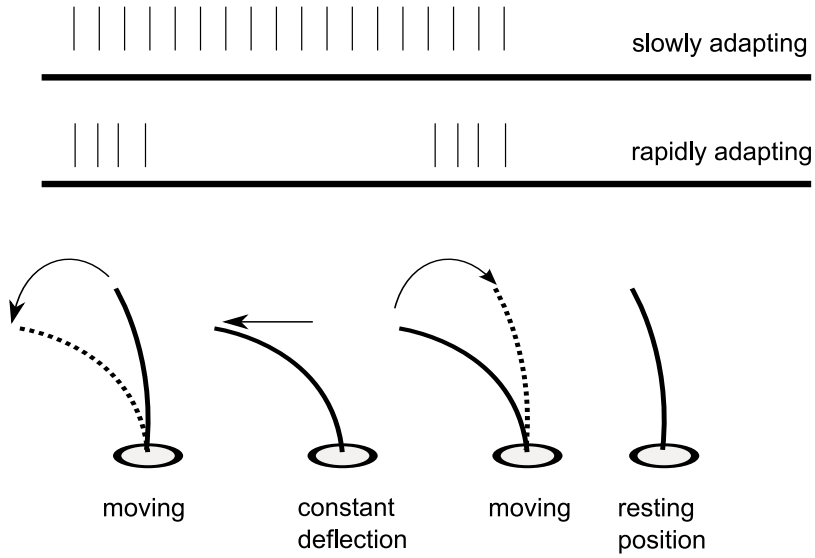


Figure 2-3: Different response patterns for rapidly and slowly adapting sensory fibres and the respective whisker motions. Moving a whisker activates both types of receptors, while a deflection from the resting position without whisker motion only activates the slowly adapting fibres. Schematic adapted from [165].

per vibration cycle [55]. Type 1 and type 2 fibres differ mainly in their response to deflection in various directions: Type 1 nerve fibres show directional sensitivity meaning that they always respond to the same motion direction during the vibratory cycle. Type 2 fibres (slowly adapting) and rapidly adapting nerve fibres both do not show directional sensitivity [55].

2.1.3 Neuroanatomy: The Whisker-To-Barrel Pathway

While in this section, we will focus on the major feed-forward connections of the whisker-to-barrel pathway, it should be kept in mind that there are many feed-back connections from the cortex to thalamus and other areas (see lower panel of figure 2-5) [116]. The neural signals from the sensory cells in the whisker follicle are passed on to the cortex of the animal via several neural stations. Since the neurophysiology is particularly well described in rats, we will limit our discussion accordingly. A schematic representation can be found in figure 2-5. The cell bodies of the sensory neurons lie in the trigeminal ganglion. A recent study confirmed that these cell bodies are arranged somatotopically [93]. The first synapses are found in the trigeminal nucleus. In this brain stem nucleus, the nerve inputs from each whisker remain separated and project topologically onto so-called *barrelettes* [78]. From the trigeminal nucleus, the signals

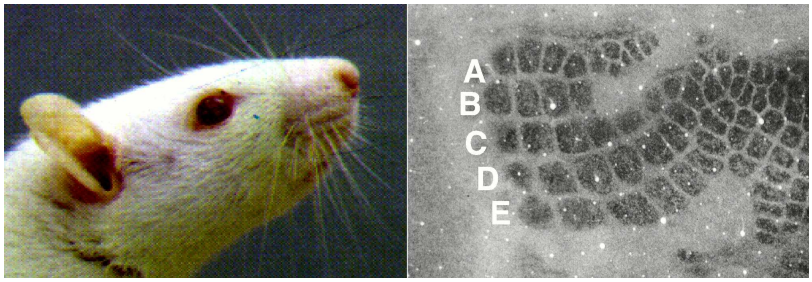


Figure 2-4: Left panel: close-up of the rat whisker pad Right panel: section through layer IV of flattened rat barrel cortex, in which the barrels of the straddlers have been airbrushed out to facilitate the labeling of the main rows (A-E). The stain is for cytochrome oxidase, a mitochondrial enzyme. The left panel is reproduced from p. 18 of Carol A. Himsel's "Rats: A Complete Pet Owner's Manual" (Barrons, 1991). The right panel is provided by Pete Land. Figure and reference reproduced with permission of Dr. Harold Kygriaz, http://www.neurobio.pitt.edu/barrels.

are passed on to two nuclei in the thalamus, namely the ventral posterior medial nucleus (VPM) and the medial division of the posterior nucleus (POm). Again, a topological separation of the whiskers has been found in VPM, namely each whisker projects onto a single *barreloid* [37]. The primary sensory input to the somatosensory cortex I (SI) comes from VPM via the lemniscal pathway. It terminates in layer 4, the first cortical area receiving whisker input. Because of its marked anatomical structure it is called *barrel cortex* [159] (see figure 2-4, right panel). Each barrel receives input from one principal whisker. Since it is topologically organized, neighbouring barrels are fed by neighbouring whiskers [155].

This distinct anatomy is readily accessible by staining and light-microscopic inspection and thus ideally suited for neurophysiological investigation (see figure 2-4, right hand picture). In subsequent layers of SI, more connections between neighbouring barrels are found and accordingly, there are more neurons which process signals from more than one whisker (see for example [109]). The secondary pathway projects from the posterior nucleus to layer 5 and layer 2/3 as well as to the septa between the barrels, but not to layer 4 [78]. Cells in POm are responsive to several whiskers and have large receptive fields (M. Diamond in [78]).

Processing of Whisker Signals in the Somatosensory Cortex

As indicated in the previous section, one of the distinct characteristics of the the whisker-to-barrel pathway is the somatotopic organization. Up to layer 4 of SI, each barrel, barreloid and barrelette receives input from one principal whisker. Neighbour-

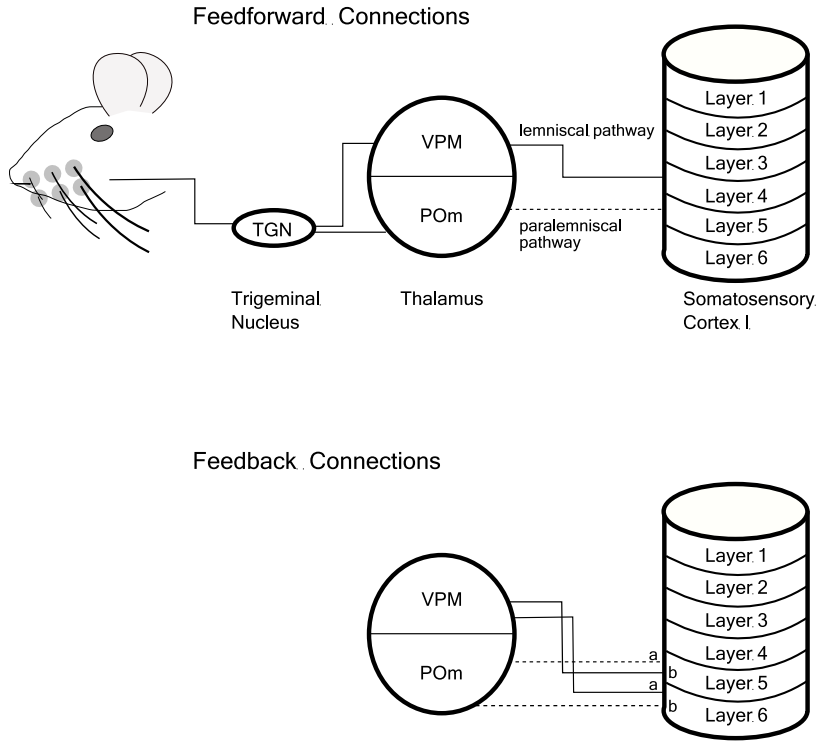


Figure 2-5: Schematic representation of the whisker-to-barrel pathway. Whisker signals from the primary afferents are first relayed at the trigeminal nucleus (TGN) to two nuclei in the thalamus, the ventral posterior medial nucleus (VPM) and the medial division of the posterior nucleus (POm). Via the lemniscal and the paralemniscal path, these two nuclei feed the somatosensory cortex I (SI). Lower panel: important feedback connections between cortex and thalamus [3].

ing barrels, barreloids and barrelettes receive input from neighbouring whiskers. The barrels of layer 4 are functionally independent in that each barrel can only be directly activated by its respective whisker [90].

Layer 4 receives most of the sensory input from the ventral posterior medial nucleus of the thalamus. Paired recordings have shown that in layer 4, synaptic connections are confined to a single barrel [43]. These connections are mostly excitatory [104] and probably serve to amplify the whisker signal before it is distributed within the cortical column for processing in subsequent layers.

The neocortical circuit of the primary somatosensory cortex shows many similarities with the basic circuitry found in the primary visual cortex (VI) [104]. The major circuitry within SI can be described as projections from layer 4 to layer 2/3, as well as to the layer 5 underneath. Layers 2 and 3 project to higher sensory areas as well as to the deep layers [104]. Layer 5 is considered the major outgoing layer

[54]. To study the spread of activation induced by stimulation of a single whisker, a microelectrode array has been used with which the whole barrel field can be sampled simultaneously. Using this methodology, Petersen and Diamond were able to show that after a very focused, initial response, activation spreads over 2-11 barrels [122]. Recently, Andermann and Moore reported a directional map within each barrel aligning direction preference of neurons in a somatotopic manner [6]. They showed that the preferred directions neurons responded to was towards the direction of the neighbouring whisker. Moreover, direction preference was more robust in layers 2/3 which the authors interpret as suggesting that the direction preference is a product of cortical processing.

2.1.4 Neural Traces of Textures

While there is a multitude of studies on the response properties of neurons in the whisker-to-barrel pathway, we will focus on the particular question of texture discrimination. During the last years, several groups have embarked on the quest for the neural correlates of textures in rats (for reviews see [102, 107]). The ability of rats to distinguish between textures of different roughness has been demonstrated to be quite remarkable, almost rivalling our finger tips in resolution [26, 56]. Among the most interesting questions are: what features can the whisker hair transduce into the follicle? What can the primary nerve cells sense and how is this basic sensory stimulation transformed and coded such that the rat can make a perceptual decision?

Starting at the periphery, two research teams have published data on the mechanical properties of rat mystacial vibrissae simultaneously. Hartmann et al [63] showed that vibrissae are strongly damped (at least under their experimental conditions). They reported resonant frequencies for whiskers between 27 and 260 Hz as the upper limits in measurements of isolated whiskers while they find lower resonant frequencies in awake animals where the whiskers were also stronger damped. Neimark et al. [113] used a slightly different protocol and stressed that they found whiskers to be underdamped. They found first mode resonance frequencies between roughly 100 and 600 Hz which increased systematically from long whiskers at the back to short whiskers in the front. Such an arrangement might serve to decompose a complex signal into its frequency components by selectively amplifying specific frequencies in different whiskers. Depending on the frequencies of the input signal, the focus of activity would thus be spatially different along the whiskers as well as in the barrel field. In a neurophysiological study, the same group reported bandpass tuning properties

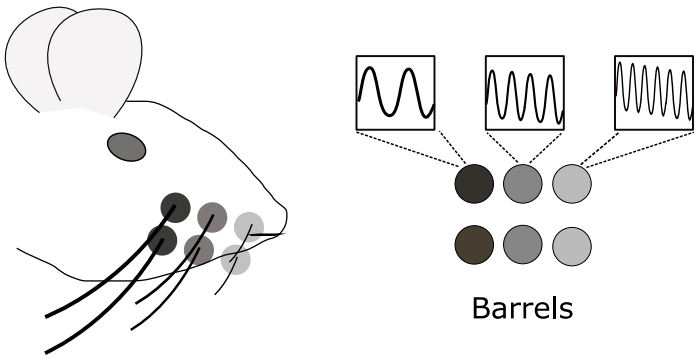


Figure 2-6: Illustration of the "resonance frequency hypothesis". On the left, the distribution of whisker lengths is schematically shown. On the right, cortical barrels are indicated. Each barrel corresponds to one whisker and thus receives stronger activation at a specific frequency range determined by the mechanical properties of the corresponding whisker. Adapted from [108].

of cells in the trigeminal nucleus and SI [7]. The authors interpreted these results as confirmation of their "resonance frequency hypothesis" [108]

An alternative to the spatial model described above has been presented by Diamond and colleagues [8–10]. They have stimulated specific whiskers with sinusoidal vibrations and simultaneously recorded neurons in the corresponding barrel in somatosensory cortex. They found that the neurons were tuned to the product of stimulation frequency and amplitude which is equivalent to velocity [8]. To extend these results to real-world textures, they recorded the whisker motion as it sweeps across a texture such as sand paper. These motions were played-back and simultaneously the activity of first-order neurons in the trigeminal nucleus as well as neurons in the barrel cortex were recorded. In contrast to the resonance frequency hypothesis described above, they find a temporal code. Neurons are shown to respond to specific kinetic features of the whisker motion [10] allowing for texture discrimination with only one whisker. Behaviorally, rats have been able to discriminate textures with only one whisker [27].

Interactions between Processing and Motor Actions

While for a long time, physiological studies have investigated response properties of neurons to passive stimulation e.g. ramp-hold stimulation, in the last years, interest has turned towards more natural stimuli. Since rats actively whisk when exploring objects and surfaces, whisking has become a focus of attention. Several studies confirm the difference in neural response between such passive stimulation and more realistic

active exploration. Szwed et al. have studied the response properties of neurons in the trigeminal nucleus by comparing passive stimulation with artificially induced active whisking. In the latter case, they find a range of cells which specifically respond to different features arising during the whisking cycle containing an encounter with an object: touch cells, and whisking cells [143]. Touch cells did not respond to whisking in free air, but only upon contact with an object, while whisking cells responded to the whisking itself regardless of the presence or absence of an object. Furthermore, Szwed et al. report the presence of whisking/touch cells and pressure cells, where the first fire both upon contact with an object and while whisking, while the latter respond to passive stimulation, e.g. rapidly applied deflections. Combining these different types of cells, several encoding schemes for object location are presented [143].

While Szwed et al. stimulated the motor nerve to mimick natural whisking, they recorded exclusively from sensory neurons. In a later study, Nguyen and Kleinfeld go one step further by assessing how vibrissal sensory signals feed back onto the vibrissa motoneurons. They show that the vibrissa trigeminal loop is an excitatory reflex arc. This loop is essentially located in the brainstem and connects the trigeminal nucleus with the facial nucleus which contains motoneurons driving extrinsic and intrinsic vibrissal muscles [114]. They find that touching an obstacle (passively or actively) increases the drive on both the intrinsic and extrinsic muscles. Stimulation of the whiskers thus strengthens exploratory whisking. The generation of whisking behavior is probably achieved by a central pattern generator [51].

First results for sensorimotor processes in higher areas are available for the primary somatosensory and motor cortex. Kleinfeld et al. have shown that sharp, rhythmic stimulation undergoes a transformation which generates a smooth, sinusoidal output in the vibrissal motor area. They speculate that such a transformation is essential to generate smooth motor control for active sensing [86].

Using artificially induced whisking in anesthetized rats has proven a powerful approach. First steps are being made to study awake and freely moving animals. Instead of electrophysiological recordings, Ferezou et al. have used voltage-sensitive dyes and a flexible fibre optic image bundle to visualize dynamics in the barrel cortex. They find that the response evoked from stimulation of the whisker was large when the animal was not whisking while it was small when the mouse activly whisking [49]. The large interest in the study of natural stimuli and the influence of sensorimotor loops connects well to the embodies approach to artificial intelligence. Given the new body of biological evidence described above, models in computational neuroscience can be refined and adapted as well as trigger new experiments in biology. The next

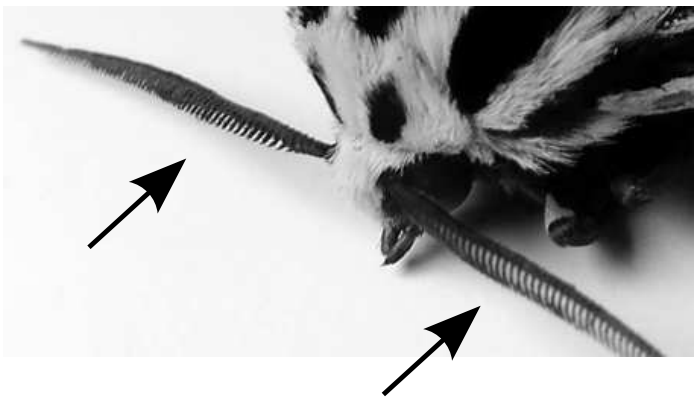


Figure 2-7: Close-up on moth antennae. The antennae are marked with arrows and show specific morphological adaptions. Adapted from wikipedia, published under the GNU public license.

important step is to work with awake animals and thus take the complete agent into account.

2.1.5 Insect Antennae - Anatomy and Touch-Related Behavior

In the robotic literature, insect antennae and whiskers are sometimes regarded as similar tactile organs. Therefore, we will give a short overview on the insect antennae with regard to their anatomy and discuss behaviors associated with antennal stimulation.

While whiskers are composed of hair and thus of essentially dead material just as nails or fur, insect antennae are part of the exosceleton of the insect body. As such they are part of the open blood system and their removal or clipping is a severe injury to the animal. The antennae are not only tactile organs, but they also bear sensory cells sensitive to smell and pheromones. An example of a species with elaborate antennae is for example the moth (figure 2-7).

Although insects are the animal kingdom containing the largest number of different species, only two examples of insect behavior based on antennae are discussed which are guided by tactile sensation. Studies in cockroaches have investigated how basic behaviors can be elicited by stimulation of antennae. One behavior associated with antennal stimulation is the escape behavior. Comer and colleagues have studied how the escape response depends on the location of stimulation. Furthermore, they were able to show that the antennae orient towards visual cues and that - if vision is

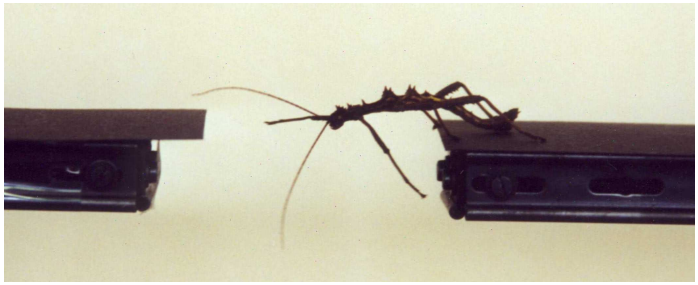


Figure 2-8: Stick insect probing for the other side of a gap. Note the extended antennae. Picture courtesy Dr. Bettina Blaesing.

blocked - the distance traveled during escape is shorter [161].

While the described escape response is a behavior which can be triggered very fast by stimulating the antenna, it is not always an appropriate behavior. In a second study, Comer and collegues [30] were able to show that the cockroach can discriminate between a fellow cockroach and a potentially dangerous spider based on tactile cues on their antenna. Different functions might be associated with different receptors but this hypothesis still needs to be confirmed. During running or walking, cockroaches use their antennae for manuvering. For example, they maintain a constant distance to walls or obstacles [25].

Another example of adaptive motion based on antennae has been studied in the stick insect. When stick insects approach a gap, they stop only when their front feet are in the air. With their antennae and their front feet, they try to locate the other side of the gap (see figure 2-8) and only if they are successful, the gap will be crossed [16].

2.2 Whiskers and Antennae - Artificial Realizations

The development of different sensors is crucial for a multitude of applications, among them robots. A machine can only be reactive if it can sense cues to react to. Therefore, a lot of effort on robot construction is spent on designing adequate sensory systems. Vision and related modalities such as infra-red sensing are commonly found. While vision is undoubtly a powerful sense, it is completely useless under some conditions such as dark or dusty environments. In these situations, tactile sensing permits to at least navigate without bumping into obstacles, and even objects and surfaces can be

distinguished.

Whiskers are an example of a tactile sense with a larger range than contact sensors on the robot body. Recently, whiskers have attracted a growing interest in the robotics community. In what follows, we will introduce various technical realizations of whiskers, some of them mounted on robots. Most of the early examples described in the following two sections, have not been developed to model natural whiskers, but are related more closely to engineering problems. In section 2.2.1, we present examples of biologically-inspired artificial whiskers, most of which have been developed in parallel and after the presentation of our artificial whisker sensor. These examples show how influential the biologically inspired approach has been, and they provide interesting suggestoins for extensions and improvements of the sensor presented in this thesis.

Binary Contact Sensors

The simplest realization of a binary contact sensor, a switch with a lever, is sometimes called a whisker. One example of such a kind of sensor can be found in the Lego Mindstorm building set. More sophisticated sensors based on a pressure sensing were described early by Will et al. [150, 158]. Their whisker was built for a gripper and they were interested in the whisker's tactile sensitivity which does not require strong forces on the object to be sensed. It was used as a binary contact sensor. As they still wanted to be able to grasp objects, the whisker was constructed such that it could retract. This mechanism was specifically aimed at industrial applications and did not refer to biological role-models. Since binary contact sensors have very limited tactile capacities, for this thesis, we were interested in whisker sensors with a broad repsonse spectrum.

Proportional Sensors

Hirose et al. [69] have experimentally built an analogue sensor based on shape memory-alloys. To detect the deformation of the whisker upon contact, they used optic sensing. The whisker sensor was mounted on the robot Titan III to determine ground proximity. Among the first proportional (i.e. not binary) whisker sensors is the construction of Jung and Zelinsky [79]. Their whisker consists of a flexible wire connected to a potentiometer. Any deformation of the wire results in a different position of the potentiometer which can be amplified and recorded (figure 2-9). The sensor was mounted on a mobile robot and used for wall-following.

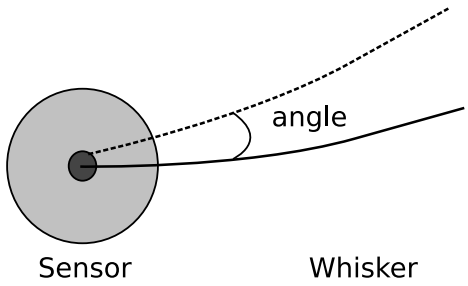


Figure 2-9: Schematic of a proportional sensor. The position of a whisker after displacement is indicated by a dashed line.The sensory unit can be e.g. a potentiometer which permits to measure the angle of displacement of the whisker from its resting position.

A similar design was realized by Russell et al [132, 133, 157]. They propose to use a single whisker on a mobile robot, in a first publication to explore objects [157] and in a later one for object location and recognition [132]. It is important to note that the whisker sensor is always touching an object with its tip. There is no description of a generalization of this method to contact points along the whisker.

Kaneko et al. [80] have developed a 3-D active antenna for sensing contact. The antenna is equipped with two position sensors and one moment sensor. While Russell in his earlier work on sensing contours [133] had to assume that the whisker touched an object with its tip, this antenna is designed to determine the point of contact by itself. To do so, it is crucial that the antenna be compliant and can bend. The basic mechanism is that the compliance of the beam is larger if the point of contact is at the end of the beam than if it is close to the base. The model is extended in [145], where contact position is estimated based on the natural frequencies of the beam. The sensor employed in this study is a torque sensor in combination with a joint position sensor at the whisker base. Both approaches depend on the active motion of the antenna.

Sensing object contours was also investigated with a new whisker sensor by Scholz and Rahn [136]. Their sensor combines an elastic beam with a hub load cell as the sensory unit at the whisker base (see figure 2-9). Again, the whisker actively sweeps across an object. From the an elastica model, the contact point is derived and enables discrimination of a circular from a rectangular shape even from different orientations. The described experiments show the potential of whiskers for precise tactile measurments. However, the tactile classification relies on internal modelling, e.g. of whisker bending.

2.2.1 Biologically Inspired Approaches

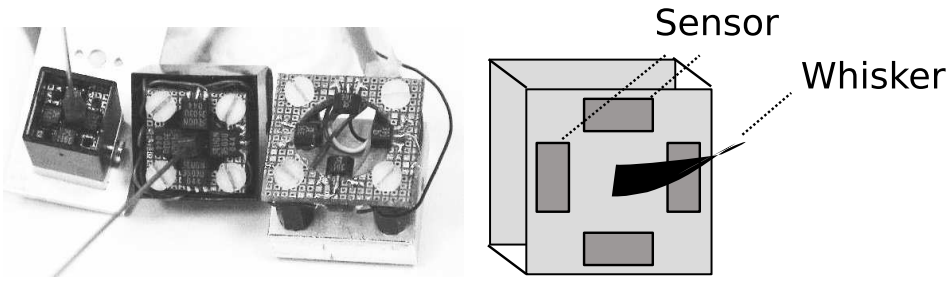
In the following paragraphs, we will describe several recent projects which developed biologically inspired whisker sensors based on different sensing technologies. Most of them were developed or published during the course of this thesis and reflect a new trend in robotics, namely to seek inspiration from natural systems.

Inspired by wall-following behavior exhibited in cockroaches which is well characterized, Cowan et al [32] developed a passive antenna based on a flex sensor. This sensor changes its electrical resistance proportional to the strain applied by bending the beam. Such a sensor is then mounted on a hexapod robot "sprawlette" and the robot is able to exhibit wall-following based on "tactile flow".

In the following approaches, researchers have been interested in perception of different features based on tactile whisker input as well as in designing a useful tactile sensor. For example, Seth et al. [138, 139] have mounted a whisker array of seven whiskers on the Darwin IX robot. Their sensor is composed of polyamid strips responsive to bending. To have responsiveness for forward and backward bend, two strips are attached back to back. The task the robot has to solve is to discriminate two different patterns of pegs attached to a wall. Based on the whiskers, the robot follows a wall. Whenever it encounters a specific pattern, an aversive stimulus is simulated triggering an avoidance reflex. The robot turns away from the wall. This aversive stimulus is elicited by a signal in the IR sensors of the robot and serves as the value signal of a reinforcement learning scheme. The whiskers deliver temporal input into a complex neural network which yields different activation patterns in response to the different timing of activation by the spatial pattern of pegs. A more detailed description and discussion of their processing follows in chapter 10.

Two groups in England have jointly worked on developing an artificial whisker sensor. First, they simulated a model of the whisker follicle [105]. As a next step, they developed a whisker sensor based on two pairs of opposing strain gauges [121] which allow the measurement of motion in 2 dimensions. They experiment with different materials for the whisker beam trying to mimick the curvature and tapering of natural whiskers, but no results or data are available at the time of writing.

After exploratory experiments on texture discrimination in rats [62], Hartmann and colleagues mounted an artificial whisker array on a rover [137]. Two types of whiskers were designed, firstly, copper wire beams with strain gages at the base of the beam which were used passively. Secondly, a whisker based on flex sensors was actively actuated. They were able to perform several perceptual tasks based on the tactile information, among them detection of ground texture, terrain features and



(a) (b)

Figure 2-10: Whisker sensors capable of measuring direction of deflection. (a) Photograph of prototypes of metal whiskers based on hall sensors. Three prototypes of different size are displayed. Four hall sensors are arranged perpendicular around the whisker base and are thus able to yield directional information. Picture reproduced from the 2nd EU Report of the AMouse project, reprinted with permission of Dr DaeEun Kim. (b) The sensors for the position of the whisker are arranged around the beam.

3-D object shape extraction.

Finally, our partners Kim and Moeller from the Artificial Mouse project have developed and evaluated a whole range of whisker sensors. As the sensing unit, they have tested magnetic sensors (as in figure 2-10(a)), light sensors measuring the shadow of the whisker beam, piezoelectric sensors, and microphone sensors. To take into account that in the whisker follicle, the whisker hair is surrounded by pressure sensitive nerve endings, they have arranged sensors around the whisker beam as illustrated schematically in figure 2-10(b) in all their designs. They could show that with a magnetic sensor, it is possible to determine the contact point of an object on the whisker [82].

Contact point information in combination with active sweeping allows to determine the shape of an object in the plane of sweeping [82]. By combining several whiskers in a two-dimensional array, three-dimensional information can be retrieved and objects of different shapes can be discriminated [84].

Kim and Moeller have also investigated the potential of different whisker sensor technologies for texture discrimination [82]. For their experiments, the whisker beam is placed onto a rotating drum which is covered with different textures. For regular configurations, they report very high reliability. For textures containing a higher degree of variance like sandpapers of different roughness, a whole range of frequencies is recorded by the whisker sensor. Comparing different rotation speeds,

whisker lengths, and magnetic versus piezoelectric sensors, Kim and Moeller found that short whiskers in combination with high turning speed and piezoelectric sensors discriminated textures best. This shows that material properties of the sensor - in this case, the whisker length - as well as an appropriate motor action - the rotation of the textured drum - are prerequisites for good data.

2.2.2 Influence of Whisker Material

So far, we have described technical realizations of whiskers. While different groups have employed a wide range of sensory devices, all have used aritificial materials as a substitute for the whisker hair. In contrast, the whisker sensor used in this thesis is based on natural rat whiskers. Lungarella et al. [98, 99] have tested different whisker materials on their response properties. The whiskers were stimulated passively by a rotating drum (see figure 2-11(a)) and the resulting data analyzed using Welch's method of spectral density estimation. Figure 2-11(b) shows response properties of four different whiskers, namely a long (caudal) and a short (rostral) rat whisker, a whisker made of human hair and one made of polyvinyl. Furthermore, Lungarella et al describe they have also tested aluminium wire, but found it to oscillate strongly as well as saturate the amplifier too quickly [98]. The response profile shows that polyvinyl fibre has strong Eigenfrequencies which are weak in the natural rat whiskers.

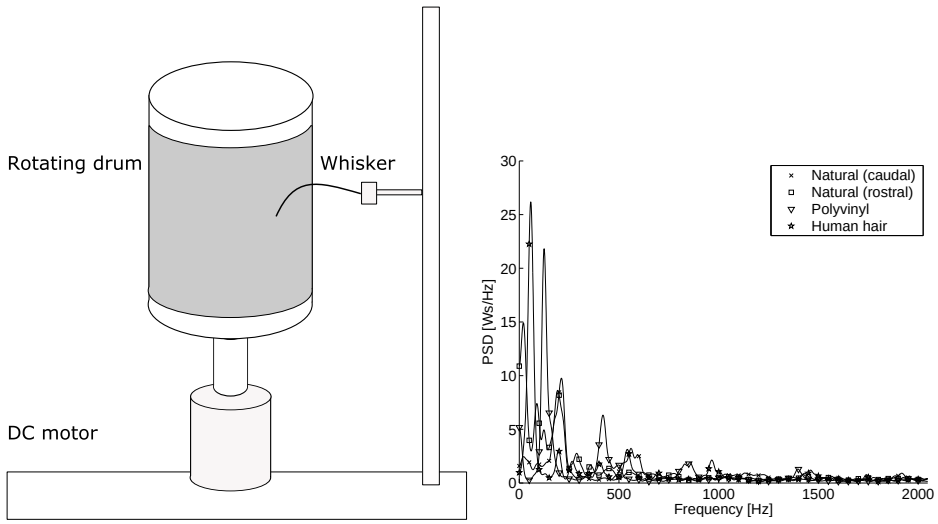
Simulation experiments on different whisker shapes suggest that the highly conical shape of the natural whisker hair plays an important role in dampening oscillations [162] (for an analysis of whisker Eigenfrequencies see also chapter 3). Moreover, Yokoi et al. have shown that a conical shape is mechanically more stable than a cylindrical one, and optimized with respect to the weight distribution along the whisker [162].

For these reasons, natural rat whiskers were used for the construction of the artificial whisker sensor for the largest part of this thesis.

2.3 Processing and Architectures

To achieve meaningful categorizations and agent behaviors, sensory data is usually processed and interpreted. Often, two steps can be identified: first the raw data is preprocessed, second a classification algorithm is fed with the preprocessed features and an output generated. Such an output can be either a purely symbolic category or a behavior in an embodied agent.

Apart from sensory categorization, the control of behavior is one of the central



(a) (b)

Figure 2-11: Investigation of different whisker materials. (a) Recording setup. Different textured materials can be fixed onto the rotating drum. (b) Power spectral density data of two whiskers (short and long), a polyvinyl fibre and human hair. Redrawn with permission from [98].

themes in artificial intelligence and robotics. We will discuss learning architectures for robots, in particular Distributed Adaptive Control (DAC).

2.3.1 Finding Meaningful Features

Raw sensory data is usually analog. First steps in processing include amplification of the signal and is often followed by analog filtering to reduce noise or eliminate frequency components which are not of interest. While the signal is analog, it is very susceptible to noise and great care has to be taken to minimize the addition of unwanted and not signal-related components. Analog to digital conversion can be either performed onboard, e.g. with specialized electronic hardware, or in a computer using for example commercially available analog to digital converters.

The result of preprocessing is usually the extraction of the relevant features which are later to be used in statistical analysis and the guidance of behavior. In this thesis, we have used spectrotemporal analysis [47, 59] as well as frequency decomposition [44, 47] of e.g. a sweep of whiskers across the surface. Similar techniques have been used by e.g. [67, 82, 137]. Recent biological evidence confirms the validity of this approach (see also section 2.1.4).

Kim and Moeller [82–84] have also computed velocity profiles as the relevant features for whisker-based tactile sensing. As discussed in section 2.1.4, neurons in the barrel cortex have been found to selectively respond to the specific velocity profiles of different textures. Since velocity mathematically corresponds to the product of amplitude and frequency, these approaches do not contradict each other but might represent different neural selectivities or experimental conditions. However, it should be noted that by applying frequency analysis, we use information transported by one single whisker. In the experiments described in this thesis, each whisker was in principle sufficient for tactile perception. This is in contrast to the resonance frequency hypothesis which states that differential responsiveness of cortical barrels across whiskers is used to extract the frequency components of a texture or object.

2.3.2 Categorization

In the context of perception, categorization is an important topic. Since this is a large field spanning psychology, neurobiology, cognitive science and artificial intelligence, we will not attempt to give a complete overview. In this context, categorization algorithms will be presented which have been applied in the context of research related to aritificial whisker sensors.

Statistical Classification Methods

There is a multitude of statistical measures and algorithms which have been developed for data analysis. Within the AMouse project, mainly two experiments have dealt with tactile whisker data on textures within an analytical approach. One of them is described in detail in chapter 8.

Secondly, a thorough study by Hipp et al. [67] compares different processing algorithms and their resulting features using several statistical classification methods. To classify different textures into a set of categories, Hipp et al. fit multidimensional Gauss distributions onto the set of training data. New data fits within one of many Gauss distributions and its class membership is thus determined.

Learning Methods in Neural Networks

In addition to the statistical methods mentioned previously, a multitude of learning algorithms have been developed which classify data based on the output of an artificial neural network. With learning, the weights between nodes are modified such that a given set of training data is well represented.

Learning methods in artificial intelligence can be grouped into supervised learning and unsupervised learning. Supervised learning depends on a teacher or the availability of complete information. The best known algorithm in supervised neural network learning is the backpropagation algorithm. It is a powerful and universal method which is widely used as a tool in classification problems. The strength of this approach is that given enough training data, this algorithm will usually perform well at classifying the given data sets and generalize to different sets. It is thus well suited to explore a given classification problem without making any claims to biologically relevant processing structures.

Since in the real world, sensory data comes without a category tag and no external teacher constantly instructs a biological agent, so-called unsupervised learning methods have been developed. We will mention two in this context, first the training of receptive fields based on objective functions, and second Hebbian learning.

Objective Functions

Efficient processing of sensory input from the real world should be well-matched to its statistical properties. Neurons should have receptive fields which respond to common features of the environment while being decorrelated so that not all neurons respond to the same input. The attractiveness of the objective function approach is that the same coding principles can be applied for several sensory systems. So far, they have been studied in the visual (for review see [81]) as well as in the auditory domain [89]. Sparse coding is explained in chapter 7, so we will limit our discussion to a second type of objective functions, the principle of temporal coherence. Within the AMouse project, Hipp et al. [68] have trained tactile receptive fields with artificial whisker data. These artificial neurons were then used to discriminate different textures. Hipp et al. have recorded sandpapers of different roughness by actively sweeping an artificial whisker across the surface. They argue that during active whisking, rats whisk the same texture several times in a row, hence the probability that two consecutive sweeps belong to the same type of texture is higher than the probability that the texture has changed. This assumption is translated into a "stability" objective function according to which the weights of cells in an artificial neural network are optimized. It should be noted that the artificial neural network in this work serves as a transformation of whisker input into activity patterns of a population of neurons. To achieve classification, i.e. to assign a class tag to a given input sweep, statistical classifiers are used and their performance is compared.

Hebbian Learning

Hebbian learning is a popular unsupervised learning algorithm. It is inspired by Hebb's seminal work "The organization of behavior" [64]. In his own words, the Hebbian learning principle is voiced as *"when an axon of cell A is near enough to excite a cell B and repeatedly and persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased"* (as found in [24]). In the context of neural network learning, this principle is translated into a learning rule where the weight between two neurons is strengthened whenever they are active simultaneously. Many variations of this learning rule have been implemented to include mechanisms which decrease the weights as well as avoid an infinite increase. We have employed Hebbian learning in experiments described in chapter 5 where we train the AMouse robot with distributed adaptive control described in the next section.

2.3.3 Behavioral Experiments: Distributed Adaptive Control (DAC)

In a purely computational approach, it is sufficient to classify previously recorded data. When working with a complete agent, this might be a necessary step, but the result of any sensory input and processing eventually has to translate into behavioral output. Topics in artificial intelligence, where behavioral models have been studied in great detail include navigation (see for example [57, 91]) and development (see for example [97]).

Most of the work presented here focusses on the robot, its capacities for complex tactile discrimination and the influence of morphology of whisker sensors on a mobile robot in reflex-driven behavior. To study the interdependence of adaptivity and morphology of whisker sensors, we have utilized a behavioral learning architecture called Distributed Adaptive Control (DAC) [125, 148]. DAC is a model for behavior which loosely imitates classical conditioning. Animals are equipped with a range of basic reflexes, a reflex being a behavior which is automatically triggered by a specfic sensory stimulation. A famous example of such a reflex is the increase in saliva production (called the Unconditioned Repsonse, US) upon the presentation of food (the Unconditioned Stimulus, US). This reflex is strong in dogs and has been the starting point for the first scientific experiment on classical conditioning by Ivan Pavlov. Pavlov consistently presented a tone (Conditioned Stimulus, CS) shortly before the presentation of food to his dog. After a number of such paired stimulations,

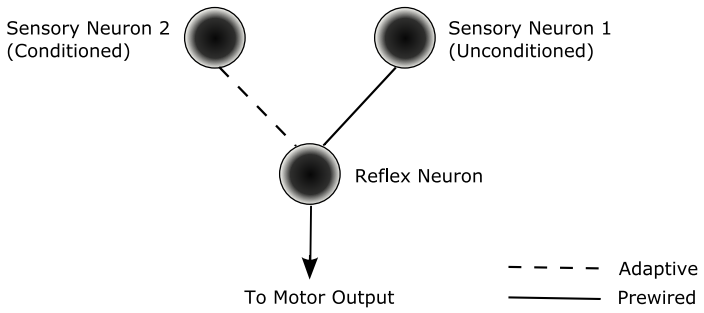


Figure 2-12: Simplified drawing of a DAC network.

the dog began to show the reflex - increased saliva production - on presentation of the tone alone. Such an association of a previously neutral stimulus with a prewired reflex is called classical conditioning.

DAC uses Hebbian learning to pair unconditioned stimuli with prewired reflexes. The agent is equipped with a set of reflexes. If the neurons triggering the reflex are active at the same time as the neurons which receive a sensory stimulus (CS), the connection between these neurons is strengthened. After repeated paired stimulation, the newly formed connection between the sensory neuron and the reflex neuron is strong enough for the sensory neuron to elicit the reflex [148]. For a schematic illustration see figure 2-12.

One of the main advantages of this architecture is that it uses few assumptions and an unsupervised and plausible learning rule, namely Hebbian learning. In the context of this thesis, it fulfilled the principle of ecological balance [125] which states that an agent's environment, sensory and motor capacities and its "brain" should be well matched in complexity. Details on the implementation and the experiments on the differences in learning of obstacle avoidance with different whisker morphologies can be found in chapter 5.

Chapter 3

Technical Realization of Active Artificial Whiskers on a Mobile Robot

In this chapter, we will describe in detail the artificial whisker sensor used throughout this thesis. We will present experiments characterizing the sensor as well as illustrate the construction of the complete AMouse robot.

3.1 Sensor Technology and Robotic Setup

As the sensing element of the artificial whisker sensor an electret condenser microphone (Four-Leaf Co. Ltd, Japan) has been used. The sensor was first introduced in [98, 99]. It consists of a microphone as the sensing device, a natural rat whisker and a small plastic roll which serves as a base for attachment.

These parts are connected with superglue (containing cyanoacrylate). The whisker is glued to the inside of the plastic support. After short drying, both are attached to the microphone membrane (for a schematic representation of the individual parts and their assembly see figure 3-1(a)). For stronger attachment, all parts are cleaned with a cotton ball soaked with ether prior to gluing.

A custom amplifier board was designed to amplify each whisker separately. The amplifier can support up to sixteen sensors. To minimize noise, the signals are amplified on the robot, and the amplified signal is sent via cable to a computer. A PCMCIA card (DaqCard 6036E, National Instruments, Austin, Texas) is used to sample and convert the analog whisker signal into a digital one (see figure 3-2).

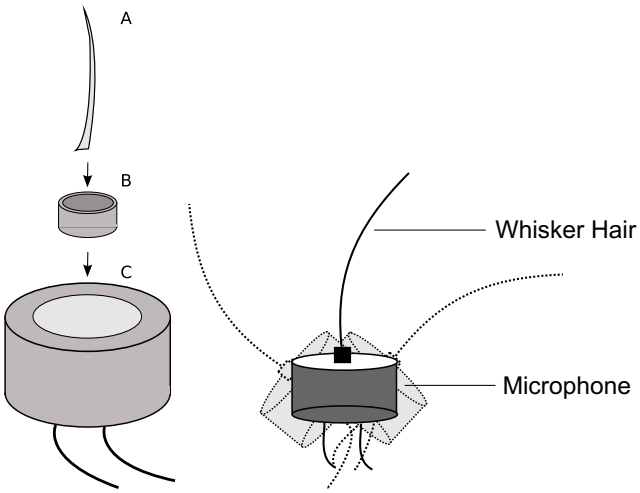


Figure 3-1: Schematic of the microphone sensor and its active movement. (a) Assembly of the microphone based whisker sensor. Parts not drawn to scale. **A** Whisker, **B** hollow plastic cylinder, and **C** microphone with cables. (b) Scheme of the movement of the whisker on the microphone, when tilted at the base. In light gray, the end positions of the whisker sensor can be seen.

Details on the modular architecture and the active sweeping mechanism can be found in chapter 3.3. Figure 3-2 summarizes the complete setup including the data acquisition and the computer. It shows that we rely on cables for data transmission. The Khepera robot platform (K-Team) is too small to carry a full computer onboard, and so we have to use an external computer. Wireless transmission does not solve the energy problems but even requires a lot of battery; therefore we have decided to use cables both for powering the sensors and the robot as well as for signal transmission.

3.2 Characterization of Whisker Properties

Rat whiskers with different lengths were tested for their resonance properties. To measure resonance, all whiskers of one array were deflected at $\approx 1.5\ cm$ from the microphone base and then released as fast as possible. During this process, data was recorded with $10kHz$ per channel (for an example see figure 3-4(a)). The time point of free oscillation was determined manually for each whisker and the corresponding data used for spectral analysis (see figure 3-3). Six different whiskers were tested, consisting of pairs of approximately equal length. Whiskers 1 and 2 were the longest

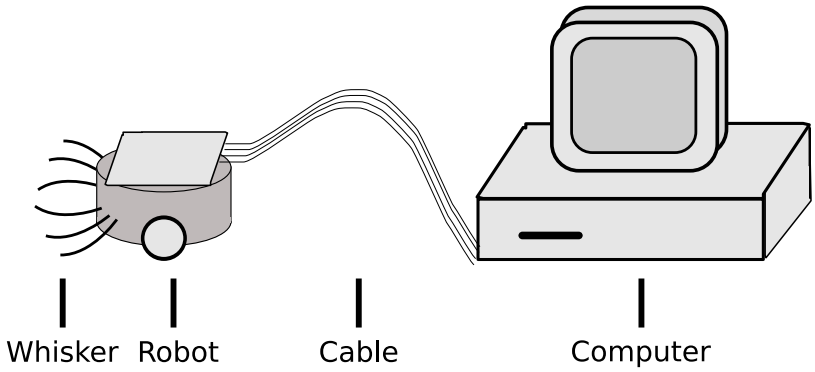


Figure 3-2: Experimental setup (simplified drawing). The robot carries the amplifier board. From the amplifier, cables transmit the whisker data onto the computer where it is processed further.

($\approx 5.2cm$), whiskers 3 and 4 were of intermediate length ($\approx 3.7cm$), and whiskers 5 and 6 were shortest (both $\approx 2.5cm$ long).

As expected, the Eigenfrequencies of the longest whiskers (1 and 2) are lowest, both for the first at around 50 Hz and for the second mode around 100 Hz. These values are in good agreement with Eigenfrequencies found by [63] and verify that the artificial whisker sensor preserves and transmits basic properties of natural rat whiskers. We have not built whiskers shorter than $\approx 2.5cm$ as they were too short for some of the robotic experiments presented in this thesis. This explains why we do not find higher Eigenfrequencies as Hartmann et al. report for the shortest whiskers. It should be noted that free oscillations after rapid release were strongest for whiskers 3 and 4, while they were hardest to determine for the long whiskers 1 and 2. Figures 3-4(a) and 3-3 also show that the whiskers return to their resting position very quickly, i.e. they are strongly damped.

3.3 Actively Moving the Whiskers

[1] Having chosen a sensor, the design of the active whisker array had to be determined. Rats can move their whiskers separately in two dimensions, but mostly they move them in synchrony and in a more or less forward/backward sweep. Since it would have been very complicated and space-consuming to equip each whisker with two degrees of freedom, our whisker array moves all whiskers synchronously in one dimension, which also facilitates motor control and the integration of motor feedback with the

[1] This section is based on [46].

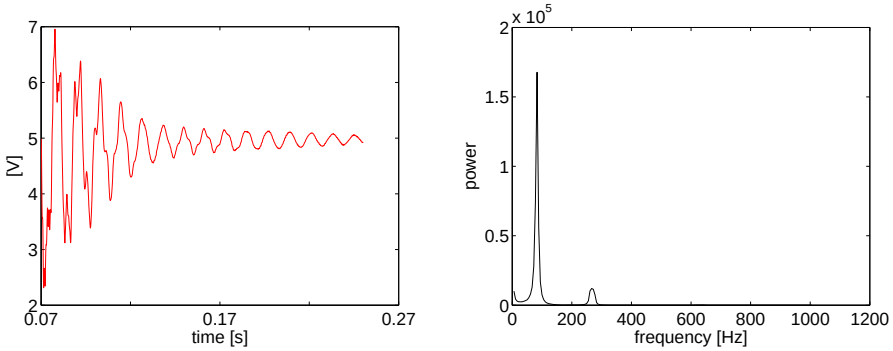


Figure 3-3: Response properties of an artificial whisker after rapid release. (a) Raw data of one channel after rapid release. This whisker was $\approx 3.7cm$ long. (b) Spectral analysis of the same whisker.

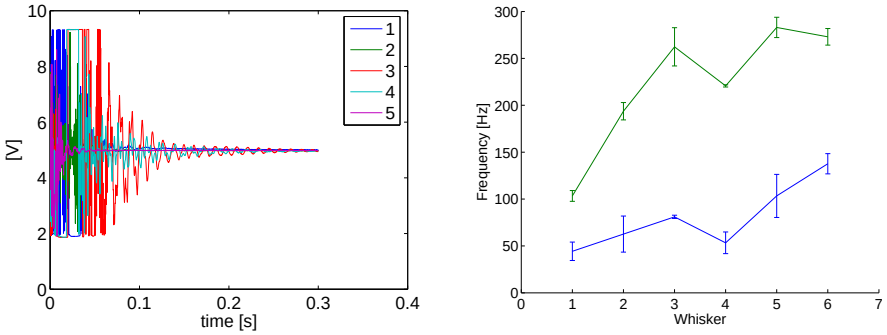
sensory signals. Predominantly, rats move their whiskers synchronously justifying our approach (for an extended discussion of active whisking in rats see section 2.1.1).

The movement pattern of the natural whiskers is a wide sweep of the tip accomplished by a small tilt of the whisker follicle. We have strived for a similar motion by tilting the microphone base of the whisker sensor (figure 3-1(b)). The angular movement achieved by our device is about 80°. The artificial whisker array consists of six whiskers arranged in two rows (figures 3-5(a) and 3-5(b)). One servomotor (Graupner, Servo DS 281) actuates one whisker array.

In order to enable easy and fast exchange of sensors within the array, the sensor is fixed on small plugs. Thus the material of the whisker, its length and orientation can easily be changed for the study of the role of morphology for signal processing and behavior.

3.3.1 The Robot Architecture

For some of our experiments we use natural rat whiskers. In order to roughly preserve the relation of body size and whisker length, we have chosen a small commercial robot platform, the Khepera robot by K-Team [106]. The Khepera is a cylindrical robot with a diameter of 6 cm, 2 motors, 8 light sensors and 8 infra-red sensors that can approximate touch sensors on the robot body. The size constraints on the robot posed some challenges on the construction part, because we had to fit the whisker arrays, the servo motors, the amplifier board and the camera on such a small robot. This problem was solved with a modular architecture, adding layers for

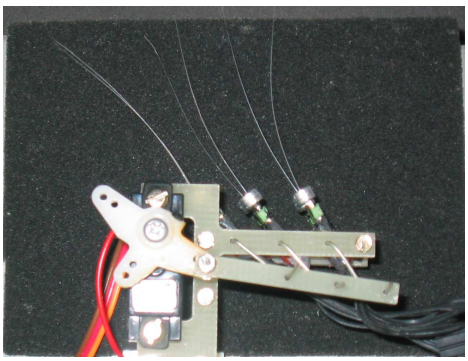


(a) (b)

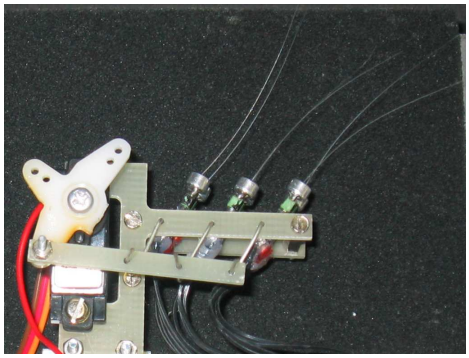
Figure 3-4: Characterization of response properties for multiple whiskers. (a) Raw data of five channels after rapid release.(b) First two mean Eigenfrequencies found for each whisker. The lower curve (blue) indicates the first, the upper (green) curve the second prominent peak.

each functionality to the robot. The first layer can be used to fix the two whisker arrays on the robot (figure 3-5(c)). These arrays can be fixed in different positions so experiments on the morphology of the whisker arrays on the robot can be conducted [48]. An omnidirectional camera using a parabolic mirror constitutes the top layer of the artificial mouse (figure 3-5(d)). An omnidirectional camera was chosen as it corresponds nicely to the wide field-of-view of mice and rats. Furthermore, we hope to be able to integrate navigational strategies developed at the Artificial Intelligence Lab in Zurich that are based on a similar camera system.

The final AMouse robot with the acoustic sensors can be seen in figure 5-1. Data acquisition and processing is done on a laptop computer to have a mobile setup for experiments at different sites and environments.



(a)



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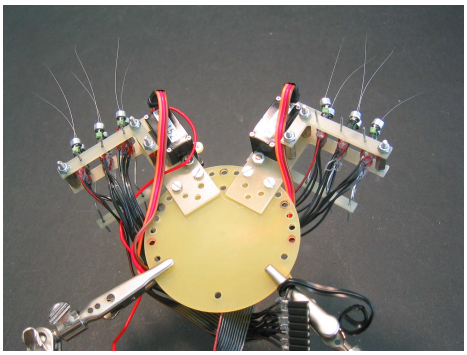
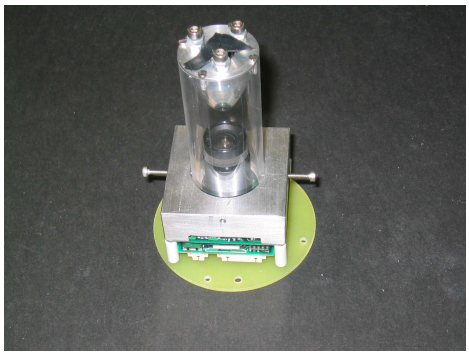


(c)



(d)

Figure 3-5: Sensory building blocks of the AMouse robot. Top row: The active whisker array. (a) Left-most position of the whiskers. (b) Right-most position of the whiskers. Bottom row: (c) Picture of the layer containing the two whisker arrays. Multiple sites are prepared for fixing the whisker arrays to allow for different morphologies (d) Camera layer with the omnidirectional camera.

Chapter 4

Optimal Morphology of a Biologically-Inspired Whisker Array on an Obstacle-Avoiding Robot

Miriam Fend, Hiroshi Yokoi and Rolf Pfeifer

Proceedings of the 7th European Conference on Artificial Life (ECAL 2003), Lecture Notes in Computer Science 2801, pages 771-780[1]

Abstract

Whiskers are versatile sensors for short-range navigation and exploration that are widespread in many animal species, especially in rodents. Their arrangement is in very precise rows and arcs on both sides of the animal's head. The controlled variations between species and the conservation within a species indicates a prominent role of their morphology for their functioning. Because of their enormous potential for robotic applications, we constructed a robot with two multi-whisker arrays, and evaluated the morphology and arrangement of the whiskers in an obstacle-avoidance task. We found that an artificial whisker array uncommon in nature performed best, and we argue that this might be explained by the other functions whiskers have in

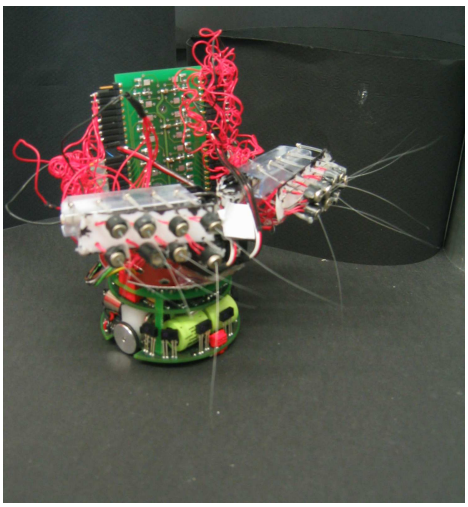


Figure 4-1: Picture of the Khepera robot with its whiskers.

animals.

4.1 Introduction

Rodents and many other animals use whiskers for exploration of close objects, and for navigating in complex environments and darkness [149]. As many of them are nocturnal animals, they have to rely on other sensory information than vision. With their whiskers, they are able to discriminate textures of different roughness by actively whisking the surfaces [26] [56]. Furthermore, animals use whiskers extensively as distance and collision sensors. Fast and easy evaluation of distances to objects is crucial when moving at high speed, e.g. when fleeing from predators or when hunting. Such evaluation of sensory information can be greatly facilitated by an appropriate morphology of the sensor distribution. Thus it is not surprising that the spatial arrangement of whiskers is highly conserved within each species, where each whisker lies on a precisely defined point in the grid of rows and arcs of the whisker pad. Additionally, the length of the whiskers always increases from the snout to the back of the animal's head [21]. The use of this arrangement has not been investigated so far and is difficult to vary experimentally in animals.

Despite their enormous potential as close-distance touch sensors that do not involve heavy contact with objects [158] [150] and that are independent of light, whiskers have not received a lot of attention from roboticists. Mainly, whiskers have been used as binary touch [164] or as strain sensors [80]. It has been shown within an engineering approach [79] that they can be used for fast obstacle avoidance on a robot, but so

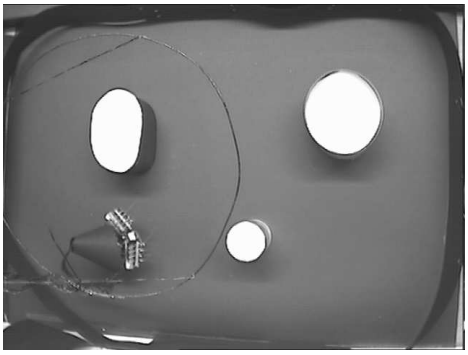


Figure 4-2: Photograph of the robot arena as seen from the overhead camera. The obstacles were marked with light paper for demonstration only. During the experiment, they were black to avoid problems with the feature tracker. The robot can be seen at its starting position in the lower left corner.

far it remains unknown, what the optimal arrangement of a whisker array on a robot is.

Since avoiding collisions is of paramount importance both in mobile robots and in animals, we used obstacle avoidance to evaluate different whisker morphologies on a robot. Obstacle avoidance is considered one of the basic behaviors in robots and has been implemented with many different methods and sensors. Many of them use vision, for example by measuring optic flow [31]. These approaches depend on an illuminated environment and often involve computationally expensive image processing. A whisker system on the other hand can work in complete darkness and will be computationally simple, if a good morphology for the sensor distribution and size is chosen.

In order to investigate what a suitable morphology of might be, we have built a multi-whisker array and mounted it on a robot. In this study, different whisker morphologies were compared as to how long each morphology moved through an experimental arena without getting stuck, and how well the free area was explored. We found that changing the morphology of the whisker array affected the performance of the robot, but interestingly the most successful arrangement was not the one commonly found in animals. A possible explanation for this result might be the multi-functionality of whiskers in nature. It may well be that the natural morphologies are a compromise between the use of whiskers as sensitive tactile organs and as fast collision detectors.

4.2 Experimental Setup

4.2.1 Hardware

The whisker sensor we use, consists of a capacitor microphone with a natural rat whisker attached to it [98]. Physical force on the whisker hair deforms the microphone membrane and results in a voltage signal different from the resting state. This signal from the microphone is amplified on the robot and sampled on an external computer.

One whisker array consists of 8 whiskers, which are arranged in two rows of four whiskers each. Two such arrays are mounted on a Khepera II robot [106] such that their orientation relative to the robot body can be adjusted within about 60°. In analogy to whiskers found in many different animal species, the length of the robot whiskers was increased from front to back in one condition (bottom row, figure 4-4), and from back to front in the other experimental condition (top row, figure 4-4). The latter does not correspond to a biological whisker array.

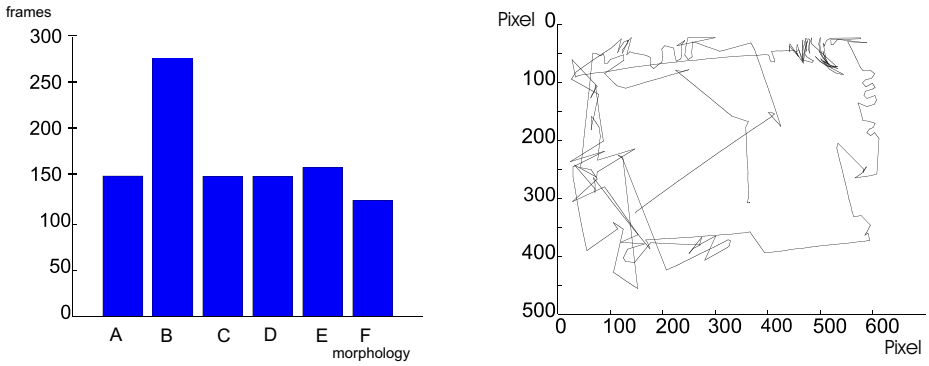
4.2.2 Experimental Environment

The robot environment consisted of an arena of 100x70cm. Inside were three obstacles of different size and shape, as shown in figure 4-2.

For every run, the robot was manually placed at the same starting position with the same orientation.

4.2.3 Control of the Robot

The robot was equipped with a simple reflex behavior similar to the classic Braitenberg vehicle [20]. By default it moved forward with constant speed. If on one side the whiskers were stimulated above threshold, the robot turned away from the stimulated side by 45°. If both whisker arrays were stimulated above threshold, the robot drove backwards for 500 ms and then turned away from the side with the higher activity value.



(a) (b)

Figure 4-3: a) Number of frames, in which the robot changed its position with respect to the previous frame. Three frames are approximately one second. b) Trajectory of one run of morphology B. The axes are labelled according to the pixel the robot was found at.

For the computation of the activity value, a baseline value for each whisker was determined at the beginning of each run. For every time-step of 62.5 ms (corresponds to 256 values per whisker), an activity value was computed for each whisker array by summing up all the differences from the baseline value. Sampling of the whisker signals was done at 4096 Hz per whisker. The parameters were chosen heuristically.

4.2.4 Tracking the Robot and Analysis

A CCD video camera was mounted above the experimental area, which was connected to a separate computer. During each run, every 300 ms a picture of 640x480 pixels was captured. The robot was marked with small, white patches that made it easily identifiable for the feature tracker. For the tracking analysis, the KLT library was used [140]. The tracking algorithm returned the (x,y) coordinates of the markers at each time step. These coordinates were used for the reconstruction of the robot trajectories, as shown in a sample trajectory in figure 4-3(b).

To quantify how well the robot moved through the whole environment, we computed the density of exploration for each morphology: We divided the arena in bins of 20x20 pixels and counted for all runs, how many times the robot was found in each bin. The results were plotted by assigning each bin a grayscale value corresponding to how often the robot was found in this bin (figure 4-5).

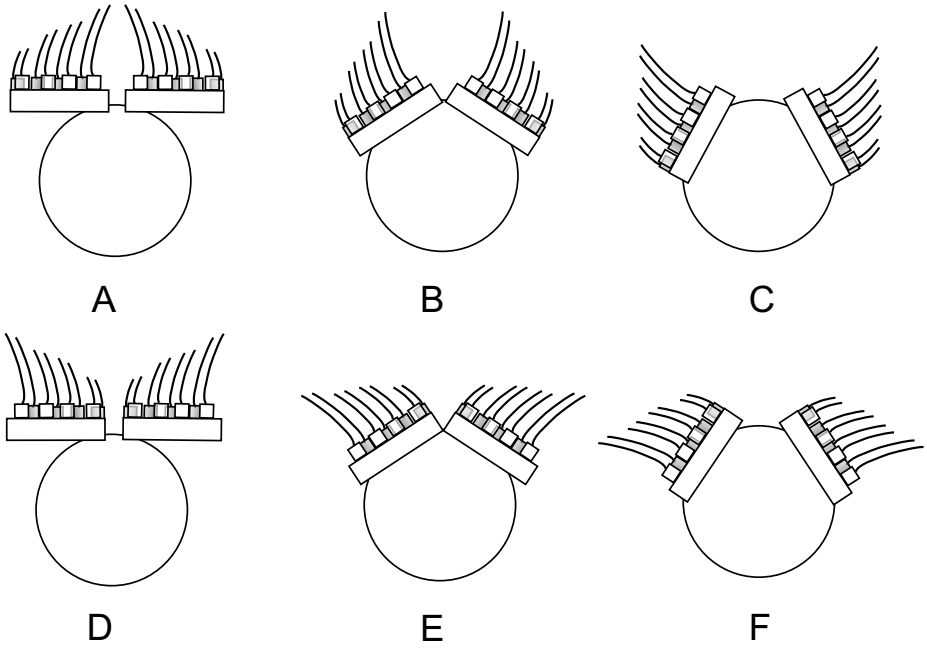


Figure 4-4: Morphologies of the whisker arrays. In the top row (**A, B, C**), the long whiskers are in the center. In the bottom row (**D, E, F**), the long whiskers are on the side, corresponding to the natural arrangement. From left to right the angle between the two arrays decreases from straight (180°) to sharp (about 60°).

4.3 Results

For the comparison of the different morphologies (figure 4-4), we defined two measures: firstly, we counted the number of frames, in which the robot changed its position (figure 4-3(a)). This number corresponds to the amount of time, the robot moved around. Secondly, we compared how well the different morphologies were able to cover the experimental area evenly. This can be seen qualitatively in the cumulated trajectories depicted in figure 4-6 and more quantitatively in the densities of exploration (figure 4-5) and in table 1. Each morphology was tested in 20 runs, always starting at the same position and with the same orientation. If the robot got stuck, the run was interrupted, but counted. If the robot did not get stuck, the run terminated after 2500 cycles of computing the activation. In the morphologies D, E and F the natural arrangement was tested, which had the longer whiskers towards the periphery or back of the robot and short whiskers in the center. For the morphologies A, B and C, the longest whiskers were in the center and the shortest whiskers pointed outwards, in contrary to what is found in biological whisker arrays. Within each of these two configurations, the angle of the whisker array with respect to the body axis

Morphology	% total area	% accessible area	> 5 entries
A	65	88	200
B	73	100	447
C	62	85	190
D	60	82	178
E	59	80	185
F	53	72	136

Table 4.1: Experimental area covered by the different robot morphologies. In the second column the whole camera image is considered. In the third column, the area that was entered by robot B was taken as the reference. In the fourth column, the number of bins is listed that each robot morphology was able to enter more than five times. This shows how evenly the different robots covered the area.

of the robot was varied from all whiskers facing to the front (A, D), a middle position with a small angle of about 20° (B, E), up to an almost parallel arrangement (C, F).

The whisker morphology B performed best on both the measures density of exploration and duration of exploration. The robot with this morphology moved around the area for about 100 s on average, whereas the robot with other morphologies moved for only ≈ 50 s. From the cumulated trajectories (figure 4-6) and the sample run in figure 4-3(b) of this robot it can be seen that robot B succeeded in covering the whole arena. In this arena, there are two narrow passages, namely in the upper left and especially the upper right corner of the arena (figure 4-2). Only robot B was able to move around the obstacle in the upper right corner. In the cumulated trajectories one can see that the morphologies E and F never even approached this narrow part, but turned away early. While all morphologies passed through the second narrow passage at least once, one can see from the trajectories that both C and F managed to do so only very few times. All figures of the trajectories (figure 4-6) and densities (figure 4-5) show a clear diagonal from the upper left to the lower right. This is the first movement of the robot at the start of each run.

Comparing the trajectories and the percentages of covered area listed in table 4.1 one can very well see differences in behavior between the morphologies. While robot B is clearly the best at moving through its environment, one can see that in general the arrangement with longer whiskers in the center of the robot gives better coverage of the experimental field. For example, the morphology with whiskers pointing straight to the front and long whiskers in the middle (A) covers 88% of the area that robot B covered. The more natural morphologies D, E and F perform worse, only between 72% and 82% of the performance of morphology B which corresponds to covering between 53% and 60% of the total experimental area.

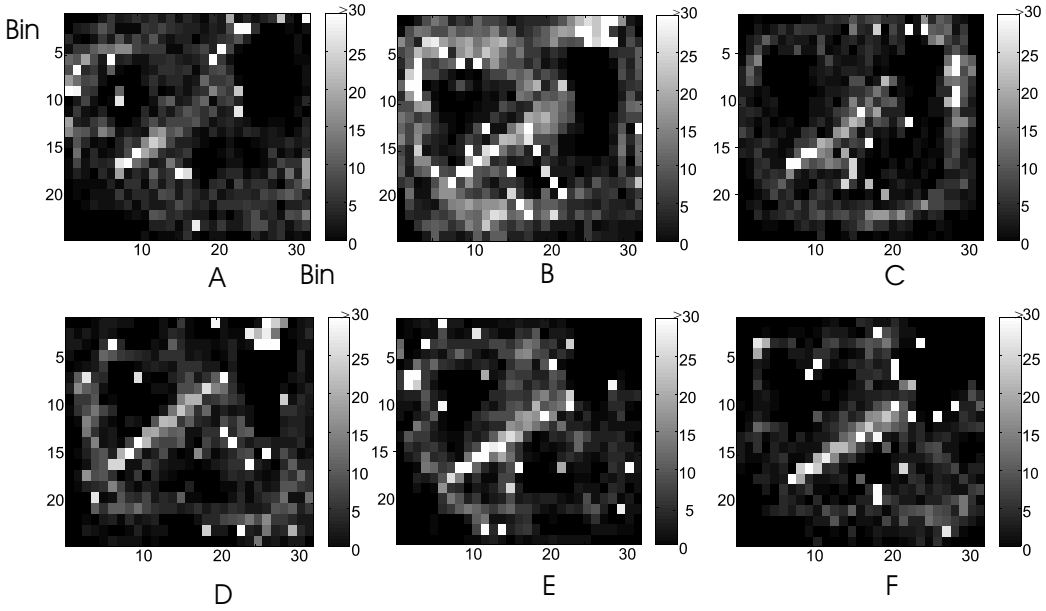


Figure 4-5: Time spent in each 20x20 pixel bin. The plots A-F correspond to the morphologies A-F in figure 4-4. On the x and y axis the bin numbers are marked.

4.4 Discussion

During the last years, biomimetic and biologically inspired robots have become more and more attractive. Several reasons account for this changed focus: on the one hand, engineers have learned to admire the refined designs and adaptivity of biological systems. On the other hand, biologists are more and more interested in using artificial systems as a testbed for their research. For example, it is almost impossible to change the arrangement of whisker sensors in mice, even though mouse genetics are the best studied mammalian genetics. To find out, why the topology of the sensors is so well preserved, why there are longer whiskers in the back and shorter whiskers in the front of the head is an intriguing question for both biologists trying to understand this sophisticated somatosensory system and for engineers concerned with building successful robots. Our experiments show that for the simple obstacle avoidance task studied, the natural morphology is not ideal. We first discuss, which features determine the performance of the robot. Then we speculate, why the morphology we found ideal for the robot is not the solution selected for whiskers during evolution.

The relevant factors for the robot performance at the obstacle avoidance task are basically the following. How fast can the robot react after it has detected an obstacle? While animals can very well adjust their speed to how well they can perceive their environment - just as we move slower when the light is fading -, the robot moves

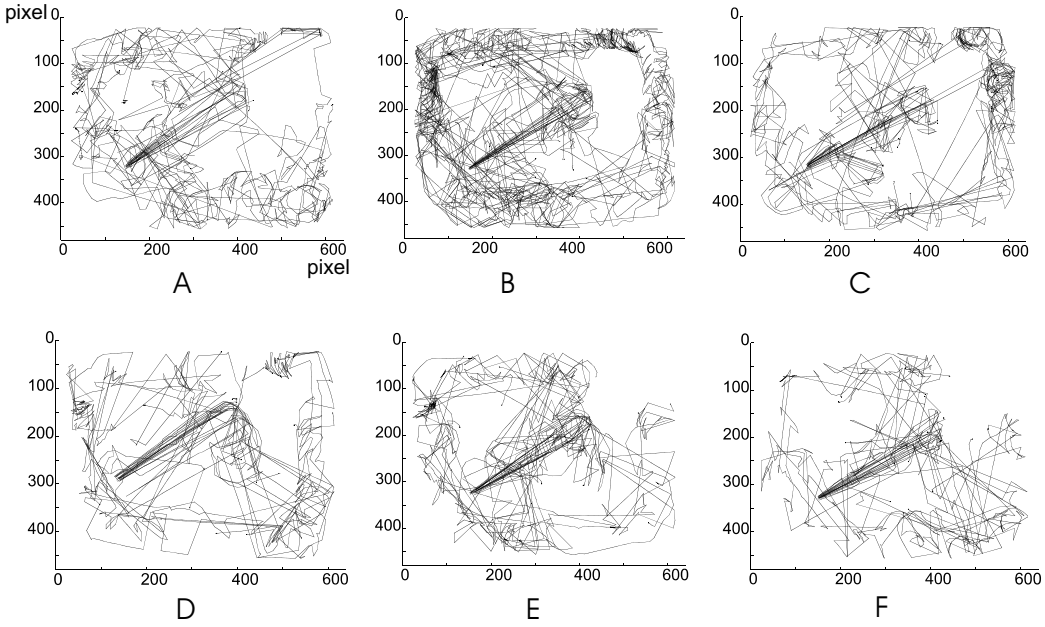


Figure 4-6: Cumulated trajectories of 20 runs for every morphology A-F. The morphologies refer to the drawings A-F in figure 4-4. On the x and y-axes, the position of the robot is indicated as the pixels of the video image. The obstacles can be identified as area never entered by the robot.

at constant speed and turns with a constant angle. For larger obstacles in its path, it often has to turn two or three times to be sure it is avoiding. So the sooner the robot detects that it is heading towards an obstacle, the better it will avoid it. Long whiskers in the front are thus advantageous (morphologies A, B and C).

When evaluating the area covered by the robot, it is also important to consider the physical space that the robot needs. This is determined by two factors. First by the dimensions of the robot itself. The straight configurations A and D for example are the widest of the six morphologies. Thus, although it was not physically impossible for them to pass through the narrow parts of the experimental area, it was more difficult. The robot can also take up more space in its sensory dimensions. This happens mainly in the morphologies C and F. Here the long whiskers point directly to the side, so even in situations, where there is still extra space for the physical dimensions of the robot, it will turn away because in its sensory world, it is already very close to an obstacle. Another shortcoming of the mostly sideways oriented morphologies is that the front of the robot is not covered very well in the sensory space. The robot often does not detect the obstacle in time to be able to react adequately. So why is the morphology ideal in our artificial system not also found in animals? What are the differences of our task with the demands in natural systems?

First, the robot relies only on the whiskers, while animals often have visual information as well. Cats for example have a very sensitive whisker system, but they also have excellent vision. Most of the time, they do not rely solely on the tactile information. Many rodents on the other hand are night-active and have very poor vision. For these species, whiskers are of high importance for their navigation. But they also use them intensively as touch organs. A closer look at the morphologies in figure 4-4 shows that morphology E, which performed poorly on the obstacle avoidance, has all the whisker tips in one plane. It is thus ideally suited for palpation of objects in the front of the animal. Since whiskers are important tactile organs for these animals, evaluating the morphology of the whisker array only as a collision sensor possibly misses features important for its other functions. Possibly, the advantages for tactile exploration outweigh the detriments of the natural whisker arrangement for obstacle avoidance. It should also be considered that most animals can move their whiskers actively. They can thus vary the exact position of their long and short whiskers much more flexibly than we can in the artificial system at the moment.

In addition to these enhanced motor capabilities, animals can also learn and adapt to different environments,while the robot controller we used did not contain any possibility of learning or evolution. It cannot be excluded that the performance of different morphologies could be improved if learning was included or different environments were used. In future experiments we will look at the interplay of whisker morphology and learning of obstacle avoidance. Artificial evolution of a simulated agent with whiskers will allow us to investigate a multitude of environments and whisker arrangements.

4.5 Conclusion

Overall it can be concluded that the whisker sensors are useful for obstacle avoidance even in narrow passages. Their use as touch sensors might require a different spatial arrangement than was found optimal for obstacle avoidance. To be able to study this aspect of behavior for the morphology, we will build an active artificial whisker array. With this active array we will also study the sensory processing of tactile perception and investigate, how distinction of surfaces and shapes can be achieved with just a couple of hairs.

Chapter 5

Morphology and Learning - A Case Study on Whiskers

Miriam Fend, Roland Abt, Marco Diefenbacher, Simon Bovet and Martin Krafft

Proceedings of the 8th International Conference on the Simulation of Adaptive Behavior (SAB), Los Angeles, July 2004, pp. 122 - 130

Abstract

In many animal species, whiskers are an important sensory modality. Rats for example navigate, explore and recognize objects by actively whisking them, seals even use them to hunt in murky water. Whiskers also make an excellent model system for biologists due to their well defined anatomy. Recently, whiskers have also attracted an increasing interest by roboticists. We have built an artificial whisker system and mounted it on a robot. In this study, we investigate the role of whisker morphology on the behavior of a robot. For a robot to be able to navigate it has to react to obstacles appropriately yet in a flexible manner. For basic behaviors, associations between reflexes and stimuli can be learned using a model of classical conditioning, the distributed adaptive control (DAC) architecture. This model of associative learning is used to correlate whisker signals with collision signals from the robot's infrared sensors for whisker-based obstacle avoidance. The morphology of the whiskers is varied to test its influence on learning and behavior. We find that the performance of the robot is clearly influenced by its morphology. Furthermore, the weights learned under different morphologies vary according to the morphology. Finally, from the performance of the robot we can speculate about a suitable weight matrix for this task.

Figure 5-1: Picture of the AMouse with its whiskers and an omnidirectional camera.

5.1 Introduction

Whiskers are a wide-spread touch sensor in biology. Although there are many animal species that have whiskers, the rat whisker system has been studied as a model system in biology for several reasons: first, rats can do amazing things with their whiskers. They can discriminate different surfaces by their textures [26][56], they can distinguish objects by their size and shape [21] and they can of course use their whiskers for local navigation. Many other animal species also use whiskers for different purposes, for example cats judge the width of openings, seals use them for hunting in murky water [36] etc.. The whisker system is also anatomically a very well defined organ: the spatial arrangement of whiskers is highly conserved within each species. Each whisker lies on a precisely defined point in the grid of rows and arcs of the whisker pad, and the length of the whiskers always increases from the snout to the back of the animal's head [21]. Additionally, a region can be identified for each whisker along the processing pathway from brainstem via thalamus to the somatosensory cortex, which processes almost exclusively input from this one whisker only. Thus somatosensory stimulation can be well defined and the brain area affected by this stimulation is fairly easy to locate.

While these reasons make the whisker system attractive to biologists, there are also good reasons for researchers in the field of artificial intelligence to be interested in the whisker system. Whiskers are a powerful sensory organ whose use for mobile robots has attracted an increasing number of scientists. There have been a num-

ber of publications on whiskers as binary touch [164] or as strain sensors [158] [150] [157], most of them inspired by insect antennae. Often, two such passive antennae were mounted on a mobile robot, or a single, active antenna was moved across different shapes [80]. Whiskers/antennae have proven suitable for fast obstacle avoidance [79] [32], but their more versatile use for texture recognition is just beginning to be recognized [47] [98] [60] [132].

In previous experiments [48], we have investigated what the optimal morphology of whiskers on a robot could be. Since the most basic behavior that can be achieved with whiskers is locally avoiding obstacles, we started with this task for the robot. The robot was equipped with two whisker arrays of eight whiskers each with lengths of 4 to 6 cm. An arrangement not commonly found in nature performed best, where the long whiskers were in the middle of the robot, short whiskers on the side. While those experiments only focused on finding a morphology best suited for the task, the robot control was purely reactive involving only a minimum of computation. The question arose, whether the disadvantages of certain morphologies could be compensated for, if learning was included.

As a learning algorithm, we use distributed adaptive control (DAC), a form of associative learning inspired by classical conditioning. Since bumping into something usually hurts the animal, it is reasonable to assume that it has a set of reflexes associated with obstacles. When such a reflex and another sensory stimulation e.g. at the whiskers are consistently elicited simultaneously, associations can be formed and the whiskers can be used as an early alert system that something is getting very close to the animals face. A more detailed description of the algorithm and its motivation is given in the following section. Applying this learning algorithm to three different whisker morphologies we have found that avoiding collisions successfully is still highly dependent on the specific arrangement of the whiskers. We also find that the weight matrices learned on average depend strongly on the morphology. Finally we speculate how animals might deal with the disadvantage of the morphology, and how we as designers have to consider morphological issues.

5.1.1 Distributed Adaptive Control (DAC): Learning with Reflexes

A wide-spread and basic form of learning in natural systems is classical conditioning. It relies on a set of preprogrammed or unconditioned reflexes that can be triggered by an unconditioned stimulus, which is a certain sensory input. With Hebbian learn-

ing, other sensory inputs can form connections with the unconditioned stimulus and eventually trigger the unconditioned reflex without presence of the unconditioned stimulus. The DAC (DAC=Distributed Adaptive Control) architecture [148] [126] is a control architecture for mobile robots inspired by a general model of conditioning [147]. To test the influence of morphology in learning and behavior, we have set up a neural network architecture using DAC that closely models the learning just described. The network is schematically shown in figure 5-2. Here, input from the robot's infrared sensors signal collision with an object. In the case of collision, the preprogrammed reflex was to turn away from the encountered obstacle. The robot receives additional sensory input from the the whisker sensors. In the beginning of each experimental run, the neurons connected to the whiskers are connected to the neurons receiving signals from the IR sensors with zero weights. But with repeated exposure to obstacles, the weights of the whisker neurons j to the neurons i that elicit the avoidance reflex, grow stronger according to:

$$\Delta w_{ij} = \eta \cdot a_j \cdot a_i \tag{5.1}$$

with the the learning rate $\eta = 0.05$ and the activities a_j and a_i of the whisker neurons and the reflex neurons respectively. The weights were kept between 0 and 1. To minimize random associations due to noise, the associated weights were diminished when a discrepancy according to the condition in equation 5.3 between whiskers and IR sensors was detected:

$$|a_j - a_{IR}| = 250 - \kappa \cdot 700 \cdot (w_{ij} - w_{iIR}) \tag{5.2}$$

$$\Delta w_{ij} = \kappa \cdot a_j \cdot a_{IR} \tag{5.3}$$

with the forgetting rate $\kappa = 0.1$, the activity a_{IR} and the weights to the reflex neurons w_{iIR} of the IR sensors. The activities of the whisker signals were normalized to values between 0 and 1000, the values in equation 3 have been determined heuristically.

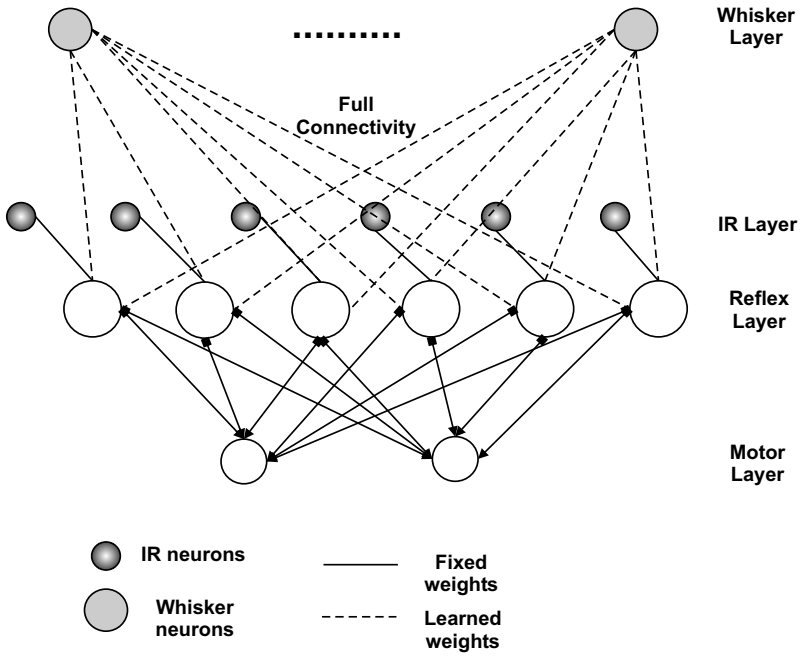


Figure 5-2: Schematic of the DAC architecture used in our experiments.

	R1	R2	R3	R4	R5	R6
motor 1	0.1	0.3	0.5	-1.0	-0.5	0.0
motor 2	0.0	-0.5	-1.0	0.5	0.3	0.1

Table 5.1: Preprogrammed weights connecting the neurons in the reflex layer (R1-R6) to the motor neurons.

5.2 The Artificial Whisker System

5.2.1 Hardware

All experiments described in this paper were done with the Artificial Mouse (AMouse) robot (figure 5-1). Designed in close cooperation with biologists and neuroscientists, this robot is based on a Khepera platform [106] with two artificial whisker arrays. The artificial whisker sensor as described by [98] consists of a natural hair glued onto the membrane of a capacitor microphone (figure 5-3). The signals from the whiskers are dynamic and of a temporal nature, the sensor is capable of transducing high frequency information. In this experiment, only a low sampling rate of 50 Hz per channel was used. The Khepera is also equipped with eight infrared sensors, which were used as collision sensors for learning of obstacle avoidance. While whiskers are tactile sensors, IR sensors measure light, so they are a kind of visual input.

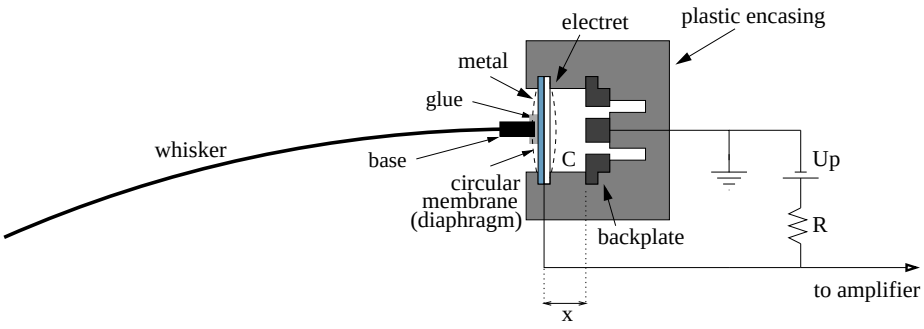
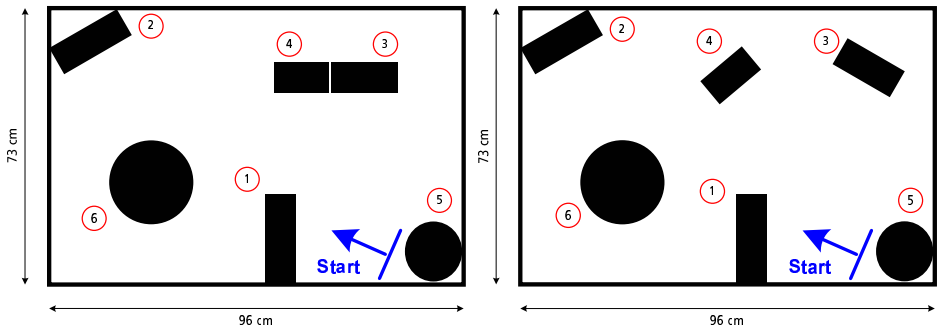


Figure 5-3: Schematic of the whisker sensor, taken from [98]



(a) (b)

Figure 5-4: Schematic of the experimental arena (a) Setup for training the robot (b) Test arena with one more tight passage in the upper right corner.

5.2.2 Experimental Setup

All experiments were conducted in a white arena of 96x73 cm. It contained several round or square obstacles of plastic and wood respectively. For some of the experiments, the training arena (figure 5-4(a)) was simplified in one corner to facilitate the formation of proper associations during learning. For each run, the robot started at the same position and with the same orientation. It explored the area for 2 min and during this learning period, the obstacle avoidance was based on the IR sensors and the forming connections with the whisker sensors. During the following testing period of maximal 3 min, the AMouse navigated only using its whiskers. If there was no stimulation of the whiskers, the robot moved forward by default.

The behavior of the robot was evaluated based on recordings with an overhead camera with two frames per second. After the experiment, the trajectories were generated by feature tracking based on the KLT library [140]. The resulting trajectories

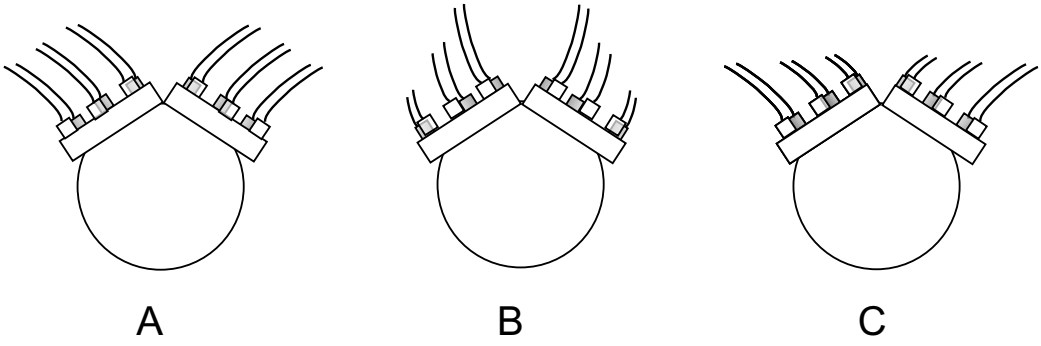


Figure 5-5: Robot morphologies. In (A), all whiskers have the same length, (B) long whiskers are in the front and (C) long whiskers on the side of the robot.

of the exploration were plotted for each experimental condition were pooled, and the resulting cumulated trajectories for all runs of the same morphology are displayed in figure 5-6. For each morphology, a minimum of 11 runs was conducted.

5.3 Results

To evaluate the influence of the whisker morphology on behavior and learning, three different robot morphologies were tested (see figure 5-5). The first morphology used whiskers of an equal length of 7 cm. The second morphology had whiskers with a length of 5, 6 and 7 cm with the longest whiskers in the front and the shortest whiskers on the side of the robot. In a previous experiment with fixed controller [48], the latter was the most successful morphology. The third morphology is the whisker arrangement also found in nature, namely long whiskers on the side and short whiskers in the front of the robot.

5.3.1 Behavioral Results

The performance of the robot at avoiding obstacles was evaluated during a 3 min exploration of the arena. The trajectories from all runs (figure 5-6) serve as a qualitative measure on how well the robot was able to explore the arena. Figure 5-6(d) shows the cumulated trajectories of 10 runs of obstacle avoidance solely based on the infrared sensors. This can be interpreted as the best possible behavior, since it provides the substrate for learning. The whisker-based behavior displayed in the plots 5-6(a), 5-6(b) and 5-6(c) shows clear differences depending on the morphologies. Only morphology 5-5A managed to drive around the round obstacle in the lower left

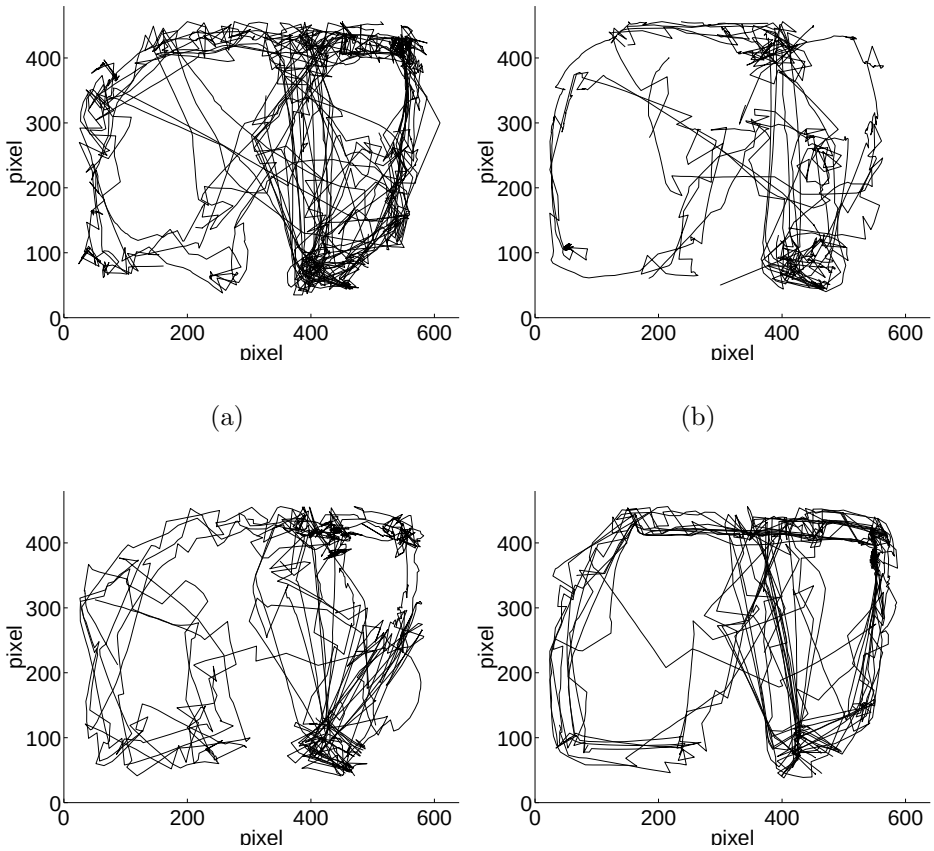


Figure 5-6: Cumulated trajectories for morphologies A(a), B(b) and C(c). (d) shows the trajectory for obstacle avoidance with IR sensors only.

and the upper right corner of the arena several times. In this area, morphology 5-5B performed worst.

A more quantitative measure for the performance of the different morphologies is the mean time that the robot moved without colliding into an obstacle. As shown in figure 5-7, the morphology A with equally long whiskers performed best when evaluating the duration before collision.

5.3.2 Analyzing Learning

Another interesting perspective on the experiment is the analysis of the learned weights. Figure 5-8 shows the different mean weight matrices for the whisker neurons to the reflex layer neurons. Figure 5-8(d) displays a weight matrix we postulated to

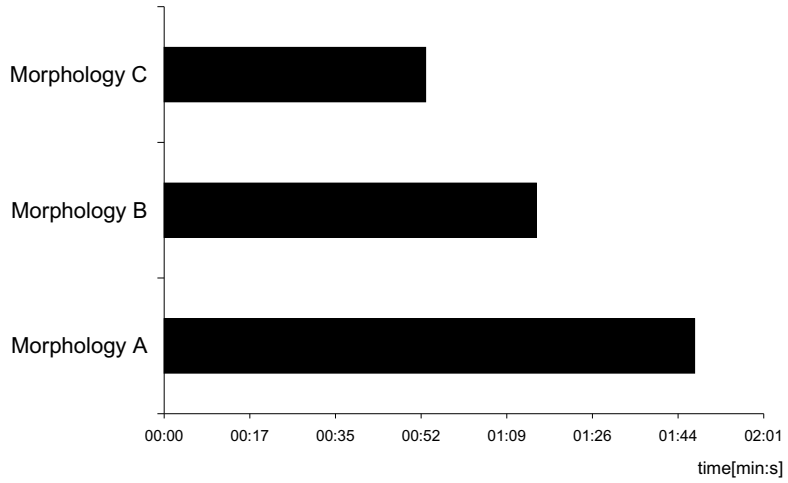
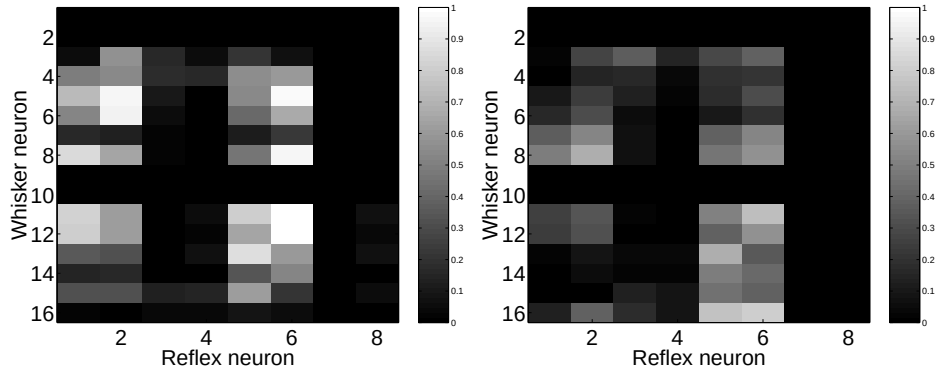


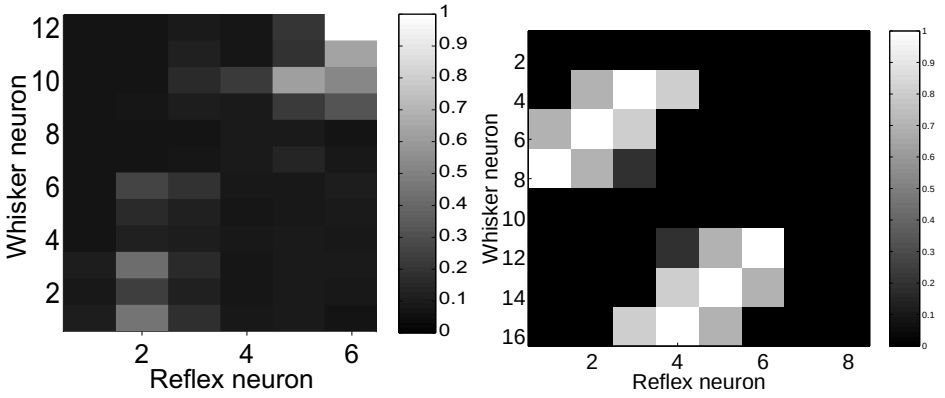
Figure 5-7: Mean time to collision for all three morphologies. Morphology A with all whiskers of equal length performed best.

emerge, if the stimulation was evenly distributed and the learning optimal. It assumes that whisker neurons can form associations only with the reflex neurons that connect to IR sensors from the same side, since these are the only ones that should be active simultaneously when encountering an obstacle. Comparing the weights in figure 5-6(c) as well as the other morphologies with these postulated weights, it becomes obvious that the natural morphology C develops weights that are most similar to the expected weight matrix.

To verify our hypothesis that these weights really are the ones learned for good performance, we analyzed the weight matrices of all morphologies with respect to the performance during testing (figure 5-9). Here, weight matrices are no longer averaged over a specific morphology, but pooled with weight matrices of similar performance. It can be seen that the weights that steered the robot longest without collision (figure 5-9(d)) are different from the expected weights in figure 5-8(d). While the postulated weights from the whisker neurons only connect to reflex neurons on the same side of the robot, the best-performing weights have connections to the contralateral reflex neurons as well. The weight pattern most similar to the postulated weights (figure 5-9(a)) actually performed worst.



(a) (b)

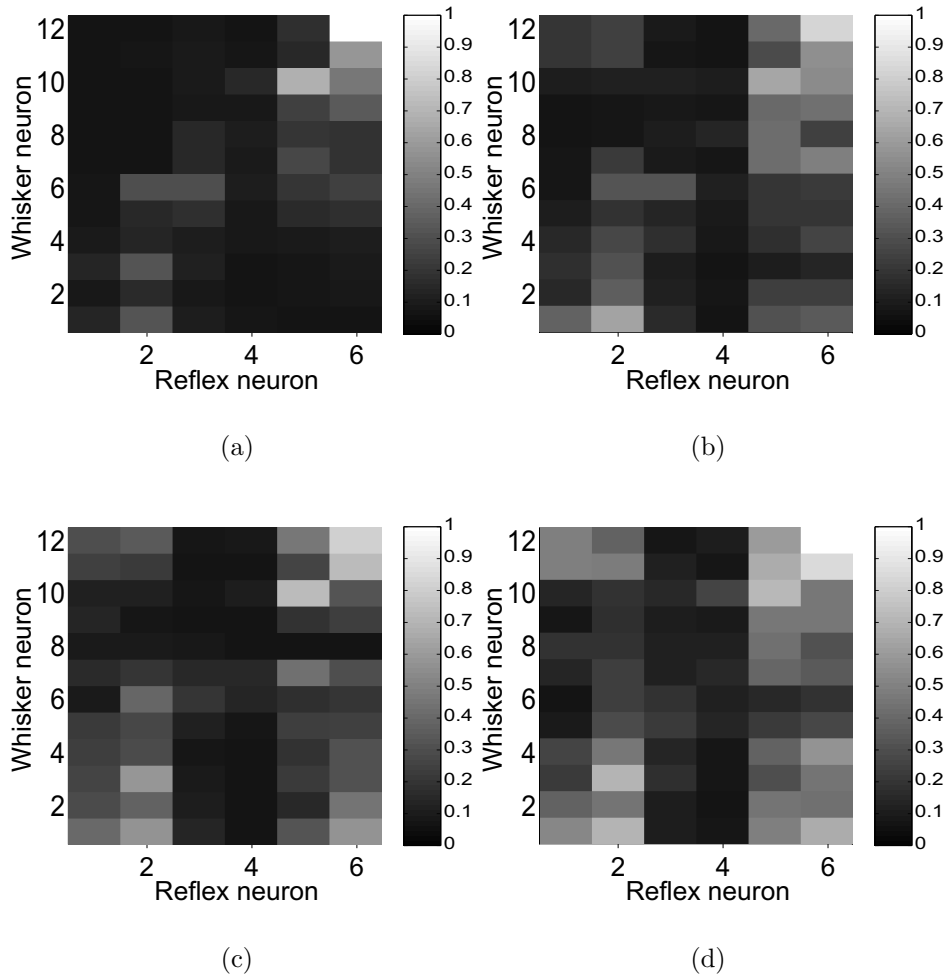


(c) (d)

Figure 5-8: Learned weight matrices for the three different morphologies (A), (B) and (C) corresponding to figure 5-5. (D) Expected weight matrix

5.4 Discussion

During the last years the importance of the physical instantiation of a behaving system has become widely recognized [125]. In the context of embodied artificial intelligence, the morphology of an agent is also considered relevant for intelligence and the adaptivity of the agent's behavior. This study investigated how learning and behavior depend on the morphology of an agent in the specific case of an agent learning how to navigate with whiskers. As in our previous experiments, the performance of the agents varied with different morphologies and certain morphologies performed better than others. The morphology commonly found in nature performed worst, when measuring how long the robot explored the area without collision (figure 5-7).



(a) (b)

(c) (d)

Figure 5-9: Weight matrices across all morphologies that were equally successful at avoiding collisions. (A) collision before 30 s (B) collision between 30 s and 1 min (C) collision between 1 and 2 min (D) collision after 2 min.

This morphology has long whiskers on the side and short whiskers in the front of the robot which poses the problem that in the main direction of movement, obstacles can only be recognized rather late. Possibly, there is not enough time left to turn completely when the obstacle is in an unfavorable position. The most successful morphology A employs equally long whiskers.

Another perspective on the performance of the robot takes into account, whether the robot managed to cover the whole experimental area. Again, morphology A showed the best performance regarding how evenly the arena was explored. Having long whiskers enables the robot to detect objects well in advance, but it could also cause a problem: If the robot has a sensory space that is far greater than the physical

space it actually needs, having a longer sensing range might result in the misinterpretation of certain tight passages as being too small. This happened in the previous study for some morphologies. There the robot's sensory dimensions in certain morphologies exceeded the physical dimensions too much, thereby preventing the robot from entering narrow spots even though it would have been able to pass through.

In the experiments described in this paper, the robot learns to elicit a set of reflexes when certain whiskers are activated. The strength of each connection as well as the pattern of connections depends on what the robot learns. Although there is no reward for fitting through tight passages during testing or learning, simply associating neurons that are active at the same time balances the longer whiskers with the lower activity of the respective IR sensors. Thus, the robot morphology most successful at moving without collisions is also most successful at passing tight spots. It proves advantageous to have long whiskers everywhere as long as the robot can learn at what level of activation it has to turn away from an obstacle.

Our study has also another aspect, which analyzes the weights learned during training. We find clear differences in the associations formed between reflex neurons and whisker neurons depending on the whisker morphologies. In advance, we hypothesized that the most reasonable associations should correspond to the matrix displayed in figure 5-8(d). Here, the association between whisker neurons and spatially corresponding reflex neurons are highest, associations to neighboring reflex neurons are weaker, but there are no associations to contralateral reflex neurons. It turned out that the weights learned in the morphology performing best did not match this expectation. Therefore, we analyzed the weights of all runs sorted by the performance of that particular controller. Surprisingly, the weight matrix performing best had strong connections to the contralateral reflex neurons. To understand the effect of whisker stimulation on the motors in a specific case, we calculated the motor values for the case of an activity of 1 for whisker 11. For the badly performing matrix in figure 5-9(a) the resulting motor values are 0.11 and -0.07 for the right and left motor respectively. The same activity pattern yields 0.11 for the right and -0.20 for the left motor when processed by the matrix with the best behavioral performance. Stronger connections to the contralateral side thus elicit a stronger backwards motion on the contralateral motor, causing a smaller turn radius. This enables the robot to react faster and to successfully manoeuver in tight space.

The experiment placed a constraint on the time available for learning. This was done for two reasons: first we wanted to evaluate which morphology was able to learn to perform well in short time. Second, constraining the learning period also made the

experiments more practicable. However, the training was too short to have perfect learning and we did some runs with significantly longer learning time that showed an increased performance. Still, the lesson from this restricted learning is that the morphology plays an important role for the acquisition of and the performance on obstacle avoidance.

But why is the natural whisker arrangement not the best for the obstacle avoidance, even though whiskers are used for this purpose by so many animal species? There are several aspects to be considered. Firstly, having long whiskers sticking out in front of the snout might be troublesome during eating. Secondly, the whisker pad of rodents for example is much denser than our robot model. Whiskers more to the back are still quite close to the snout, whereas in our robot, the whiskers are much further apart making there position more important. Most probably though, two other aspects are more prominent: as already described, whiskers have more functions than distance sensing, they are also a powerful touch organ. For tactile exploration, the natural morphology might be advantageous, because all the whisker tips lie in a plane. Objects can thus be whisked simultaneously by a maximal number of whiskers yielding rich information. Lastly, animals can move their whiskers actively and thus change their orientation dramatically. If necessary, a rat can point its whiskers actively to the front. We have not yet incorporated a flexibility in the morphology that is dependent on the behavioral state of the agent.

To conclude, the morphology of sensor arrangement is of paramount importance for the design of successful artificial agents. In this case study, it was not possible to compensate a slightly disadvantageous morphology with learning. Instead, the learning of the association of basic reflexes was strongly dependent on an appropriate morphology.

5.5 Conclusion and Future Work

In the experiments described, DAC proved to be a valid algorithm for learning whisker-based obstacle avoidance. In previous experiments, an unnatural whisker morphology turned out to be advantageous for obstacle avoidance. This time we tested whether this disadvantage of the natural arrangement would persist when the robot could learn. We found that using a restricted learning period, having equally long whiskers was advantageous. Furthermore and against our intuition, the most successful weight matrix for the task involved strong contralateral connections between whiskers and reflex neurons. In future work, we will investigate other functions

of whiskers such as texture recognition and object exploration. For more advanced behaviors, vision will be integrated and the interaction between different sensory modalities will hopefully yield interesting behaviors not possible with a single sensory modality.

Chapter 6

On the Influence of Morphology of Tactile Sensors for Behavior and Control

Miriam Fend, Simon Bovet and Rolf Pfeifer

To appear in: Robotics and Autonomous Systems, Special Issue on Passive Dynamics, Morphology and Control

Abstract

Many different animal species rely on whiskers for a variety of tasks. Among the most basic are obstacle avoidance and wall-following. We show that fast and reliable evaluation of distances can be greatly improved by an appropriate sensory morphology that matches the physical space of the agent. To investigate morphologies and material properties of whiskers, we conduct experiments both on a real robot and in simulation using artificial evolution. We find that the morphology most successful at following a wall strongly resembles natural whisker morphologies. This can be better understood by considering the relation of the agent body to its tactile sensing range, as well as the challenges of various tasks faced by agents endowed with different sensory modalities.

6.1 Introduction

The interdependence of morphology and control has attracted increased interest for the design of robots [29, 76] and sensory systems [48, 96]. While most sensory studies

have focused on vision, a tactile sensor has drawn more attention recently, namely the whiskers. Whiskers have been a model system for tactile sensing in biological research for a long time (for an overview see [78]). Animals use whiskers for a variety of functions: rats use them not only as contact and distance sensors, but also to distinguish shapes [21] and surface structures [26, 56]. With their whiskers, walruses search sandy ground for food such as mussels while seals can follow small turbulences generated by fish for hunting [36]. Whiskers are a powerful complement to vision because they are independent of light and visibility conditions. Natural examples demonstrate their versatile usefulness and extensive research on rats has revealed that the morphology of the whisker pad is highly conserved across individuals. The regular arrangement of the facial whiskers in rows and arcs with constant numbers is mirrored at different processing stages in the rat brain: at the brainstem, the thalamus and the primary somatosensory cortex, the neuronal ensembles fed by sensory input from the whiskers show the same structure. Each whisker feeds a dedicated ensemble of neurons called *barrel*. The anatomical arrangement of the barrels preserves the topological relations of the peripheral sensors (for a detailed description of the rat whisker system see [78]).

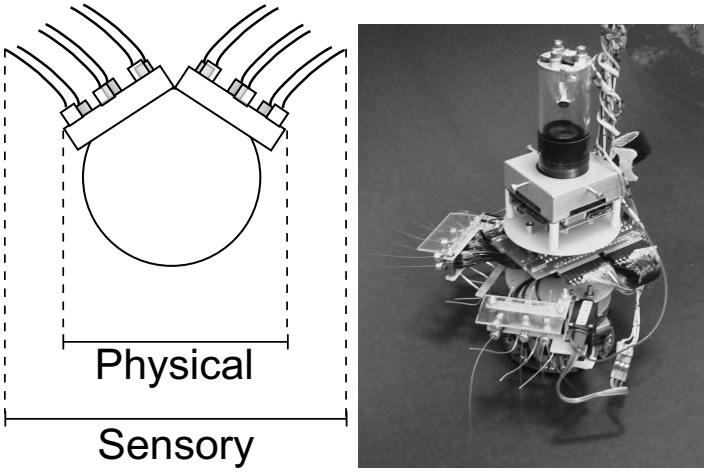
Whiskers do not only appear on the animal snout, but also on other body locations. Cats for example have whiskers on top of their eyes. Even more astonishing is a different animal species, the naked mole-rat. It has whisker-like hair on its whole body and is (almost) blind. The naked mole-rat lives in underground colonies. It feeds on roots and therefore hardly ever leaves its burrows. Experiments have shown that stimulation of their body whiskers elicits turning behavior coordinated by the location of stimulation [33]. In these animals, the location and arrangement of the tactile hairs on the body is also highly regular so that the position of stimulation is an important orientational cue for the animal.

Tactile sensors are not only useful for biological agents, but they also have great potential for robots. Indeed, several research groups have developed artificial whisker or antenna sensors in the last few years. Simple whiskers have been constructed that use a flexible beam and measure the base deflection with a switch or a piezoelectric element [79, 150, 158]. More recently, three approaches to the sensor design seem to be dominant: measuring deflection forces at the whisker base [32, 80, 132, 133, 136–138, 157], magnetic sensors measuring the displacement of the whisker [82] and microphone-based sensors with natural rat whiskers [45, 46, 98]. Whiskers have a wide range of functions as well. The simplest is binary contact sensing as for example in [32, 48, 79]. More interesting are various studies that show the potential for different

discrimination tasks. Kaneko *et al.* [80], Kim and Moeller [82] and Schultz *et al.* [137] have shown that it is possible to estimate the contact point and thereby the distance to an object with their respective technologies. Schultz *et al.* [137] report that they can reconstruct the threedimensional shape of an object using artificial whiskers. Finally, texture discrimination has been studied both in rats (see above) and on robots [44, 47, 82, 137, 138].

Some studies have only considered whisker sensors in a static setup, others have placed two or more whiskers on a mobile robot platform according to engineering-related *a priori* assumptions of a useful arrangement. With the present experiments we want to investigate the relation between the morphology of the sensor distribution on the robot body and different tasks. Inspired by the highly conserved whisker morphologies in different whisker-bearing species (see above), we ask whether specific whisker arrangements are advantageous for basic navigation tasks, such as obstacle avoidance or wall-following. The underlying reasoning is derived not only from biological examples but also from the concept of "morphological computation" [124]. The idea is to reduce the amount of processing in the "brain" of the agent using an appropriate morphology of the sensors. The control of the agent should thus be very simple. Figure 6-1(a) illustrates the relation between sensors and body. The figure shows a simplified drawing of the robot with whiskers extending to the side and the front of the body. Since these whiskers are of flexible material very similar to hair on our body, they bend away easily when the robot approaches an obstacle. By doing so, they generate a signal in the sensors placed at the root of each whisker. Depending on the length and orientation of the whisker hair, this signal will be elicited at quite some distance between the rigid robot body and the obstacle. The sensory space that the robot perceives with the whisker is therefore larger than the space it physically occupies. The relation of the physical to the sensory space will thus be important for how close the robot can approach an object.

To find an appropriate sensory distribution for our robotic agent (Figure 6-1(b)), we conduct four experiments. First, we test three different morphologies of artificial whiskers mounted on a robotic agent. The agent's task consists of avoiding obstacles while maneuvering through its arena. Emphasis is put on a simple, purely reactive controller. In a second series of experiments, we provide a learning algorithm to the controller and evaluate how the whisker morphology influences the robot on obstacle avoidance performance. To optimize both the controller and the morphology of the whiskers at the same time, we then use artificial evolution on a simulated agent. In the last experiment, we evaluate the same morphologies as in the first two robot



(a) (b)

Figure 6-1: (a) Distinction between solid physical dimensions and compliant sensory space in which the agent can sense its surroundings. (b) Picture of the robot with its whiskers and an omnidirectional camera. For the experiments described here, the camera is not used.

experiments on a different task, namely wall following.

We show that in each case, a specific morphology turns out to significantly increase the performance of the robot. Finally we discuss how our results can lead to hypotheses about the different sensory morphologies found on natural agents.

6.2 Robot and Morphologies

We use a whisker sensor based on a capacitor microphone with natural hair glued to the membrane [46, 98]. Physical force on the hair deforms the microphone membrane. The resulting voltage change is amplified on the robot and digitized on an external computer. Six whiskers arranged in two rows of three whiskers constitute one whisker array. Whiskers in the same column have approximately the same length. Two such arrays are mounted on a Khepera II robot [106]. We systematically varied the length of the whiskers with respect to their location on the robot body. The three morphologies we tested on the robot are shown in Figure 6-2. Morphology A has long whiskers in the front of the body and shorter whiskers laterally. Morphology B is an intermediate morphology with equally long whiskers both to the front and to the sides of the robot. In contrast, morphology C has the long whiskers laterally and

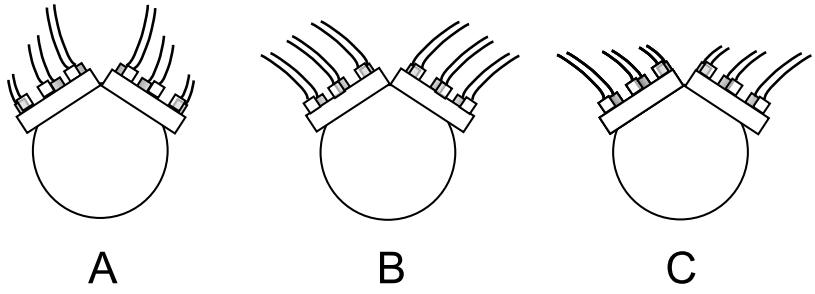


Figure 6-2: Illustration of the different robot morphologies used in the robot experiments. Morphology A has long whiskers in the front and short whiskers to the sides. This is reversed in morphology C which has long whiskers to the side and short whiskers to the front. Morphology B is an intermediate morphology with equally long whiskers to the front and sides.

short whiskers towards the robot front. This last morphology most closely resembles the whisker morphology found in most animals [21].

6.3 Experiments

6.3.1 Experiment 1: Reactive Obstacle Avoidance

The focus of experiment 1 is to find a morphology that allows a robot to navigate across an arena without hitting obstacles and to negotiate narrow passages, i.e. to cover the whole arena evenly. In this experiment, the control of the robot is deliberately very simple and not adaptive. The performance of the robot is evaluated by how evenly the experimental space is covered and how much the robot wiggles, i.e. how often the robot changes direction. Experiments are conducted in an arena of approximately 100x80 cm with several obstacles (Figure 6-3). Before each run, the robot is manually placed at a different starting position.

Robot Control

The control for the robot consists in a reflex behavior. By default it moves forward with constant speed. If on one side the whiskers are stimulated above threshold, the robot turns away by 45°. If both whisker arrays are stimulated above threshold, the robot drives backwards and then turns away from the side with the highest activity value. For the computation of the activity value, the maximum noise in each whisker is determined at the beginning of each run and the threshold set to three times the

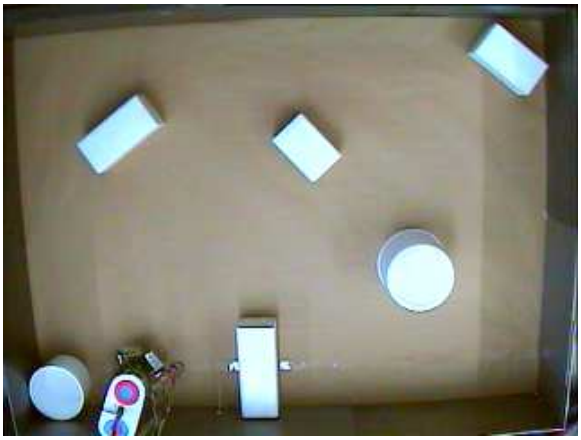


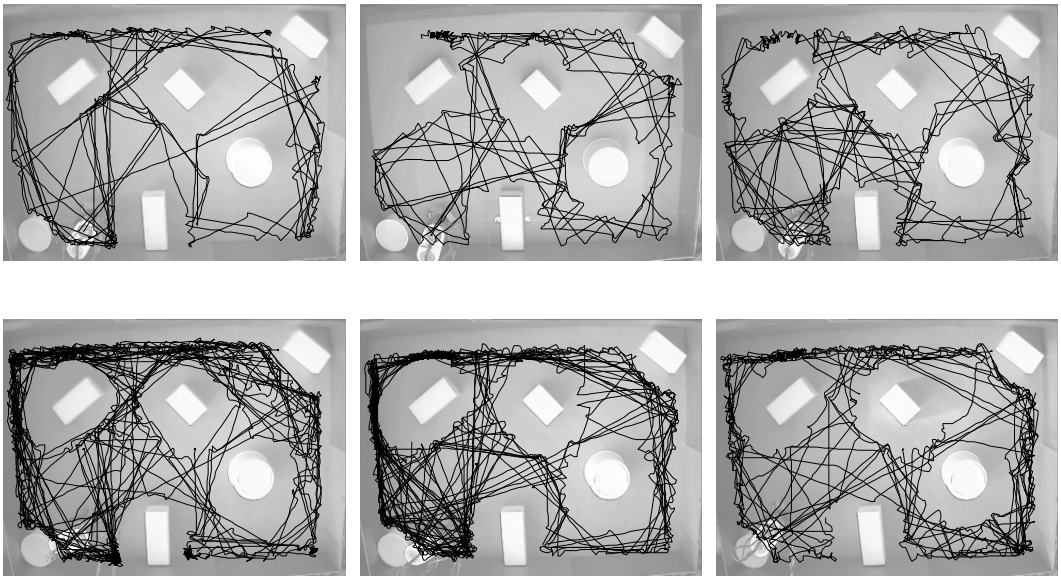
Figure 6-3: Experimental robot arena as seen from the overhead camera with the robot in the lower left corner. Obstacles can be seen as white objects.

maximum noise. For every time-step of 200 ms, the maximum absolute difference from baseline determines whether a whisker is stimulated above threshold. If at least two whiskers in one array are thus active, the avoidance reflex is elicited. Sampling of the whisker signals is done at 10 kHz. These parameters are chosen heuristically such that the robot shows acceptable obstacle avoidance. If the robot does not get stuck, the run terminated after 10′000 cycles of computing the activation corresponding to approximately $300s$.

Results of Experiment 1

To evaluate the performance of the robot, each run is recorded with an overhead camera at 2 frames per second and salient markers on the robot are tracked. The resulting trajectories allow the evaluation of each robot morphology on two aspects: first, how evenly the area is covered over all runs of one morphology, and second, how often the robot changes direction. Wiggling abounds for example if the robot is functionally blocked in a tight passage.

Even coverage of the arena can be seen qualitatively in the top row of Figure 6-4, where five runs are plotted in order to allow the distinction of single trajectories. In the bottom row, the cumulated trajectories of 10 runs are shown for each morphology. To have a quantitative measure of how evenly the arena is covered, we calculate the entropy of position distribution. The camera image is used for tracking is split in 120x160 bins. The number of entries of the robot into each bin is counted. For each bin $a \in E$, the probability $p(a)$ of the robot entering this bin is calculated from all trajectories. The entropy H over the set E is computed as:



(d) Morphology A (e) Morphology B (f) Morphology C

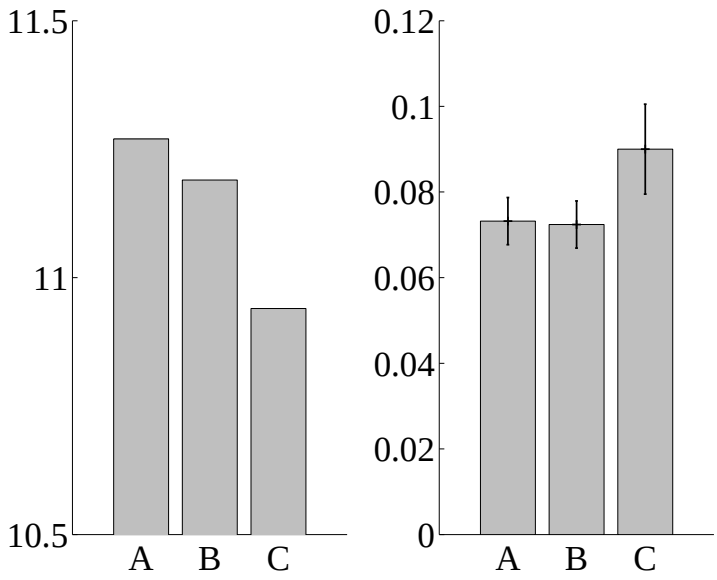
Figure 6-4: Qualitative results of Experiment 1. Top row: Cumulated trajectories of 5 runs for the three different morphologies. Bottom row: 10 runs of the different morphologies. The differences around the obstacle in the upper left corner can be seen best in the top row. Morphologies B and C show a large amount of turning at both narrow spots indicating difficulties in entering or leaving the corner behind the obstacle.

$$H = -\sum_{a \in E} p(a) \log_2 p(a) \quad \text{with} \quad \sum_{a \in E} p(a) = 1 \tag{6.1}$$

A higher entropy corresponds to a more uniform exploration of the experimental area.

The arena contains two narrow passages, namely around the rectangular obstacle in the upper left corner. Around these narrow spots, the largest differences can be observed (Figure 6-4). With morphology A, the robot passes through the corner several times without much difficulty. On the other hand, morphologies B and C pass rarely or not at all. These differences in spatial coverage can be quantified by measuring the entropy. Figure 6-5(a) shows that morphology A achieves the highest entropy, and morphology C performs worst.

When approaching the narrow spot, the robot receives alternating stimulation on both sides resulting in constant change of direction. This can be seen in the trajectories. To quantitatively account for this behavior, we compute the amount of



(a) (b)

Figure 6-5: Quantitative results of Experiment 1. (a) Entropy of spatial distribution and (b) mean amount of wiggle in morphologies A, B, and C.

wiggle defined as

$$W = \sqrt{\sum_i (a_{i+1} - a_i)^2}, \quad a_i = \text{atan}\left(\frac{y_{i+1} - y_i}{x_{i+1} - x_i}\right) \tag{6.2}$$

Figure 6-5(b) shows no difference between morphology A and B, but morphology C wiggles more, meaning that it changes direction more often even turning on the spot in narrow passages.

6.3.2 Experiment 2: Learning of Obstacle Avoidance on the Robot

In order to take into account the fact that natural agents are highly adaptive, we implement in this experiment a basic learning architecture (described in detail below) to test whether the morphology of the whiskers still influences the performance of an adaptive agent on obstacle avoidance.

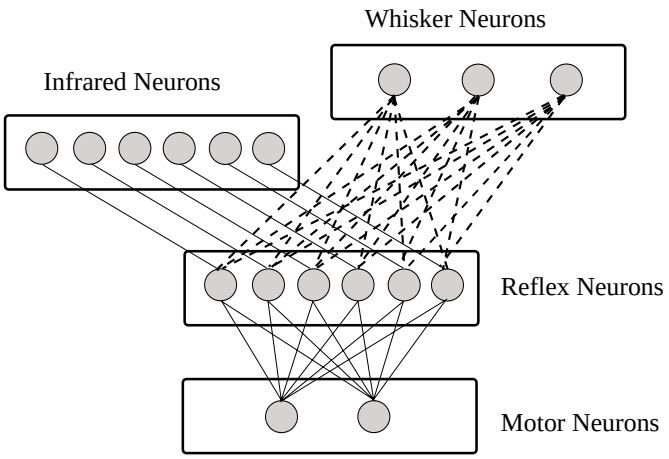


Figure 6-6: A schematic representation of the DAC network. Solid lines represent fixed weights corresponding to the pre-wired reflexes. Dashed lines represent weights which are modified by learning. The infrared neurons are connected to the reflex neurons one by one, whisker neurons are potentially fully connected to the reflex neurons. For clarity, only a small number of whisker neurons is shown.

Distributed Adaptive Control and Experimental Procedure

As learning algorithm, the Distributed Adaptive Control (DAC, [126, 148]) is implemented. This control architecture is a form of classical conditioning using a set of hardwired reflexes that are associated to unconditioned sensory stimulation. The general architecture of the network is depicted in Figure 6-6. The weights, initially set to zero, are modified according to the following Hebbian learning rule:

$$\Delta w_{ij} = \eta \cdot a_j \cdot a_i \tag{6.3}$$

where $\eta > 0$ is the learning rate and a_i and a_j are the activities of the reflex neuron i and the whisker neuron j respectively. The weights w_{ij} are clamped to a maximum value of 1. Additionally, a small forgetting term is implemented to reduce associations due to noise.

Here, the pre-wired reflex consists of an obstacle avoidance reflex using infrared sensors. Initially, no connections exist between the motors and the whiskers and the robot navigates with infrared sensors only. By repeated correlated activity in whisker sensors and infrared sensors, connections are formed such that eventually, the avoidance reflex can be triggered solely by activity in the whisker sensor.

Since the infrared sensors are read with 50 Hz, the same sampling frequency is used to acquire sensory information from the whiskers. Because of variation in the

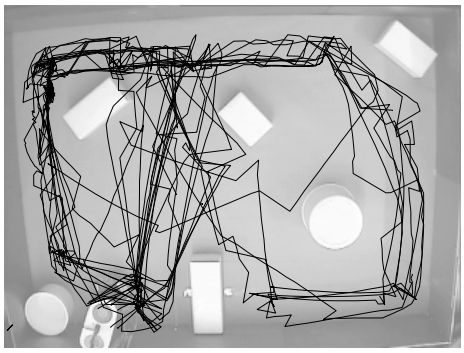


Figure 6-7: Trajectory of the robot avoiding obstacles using IR sensors only.

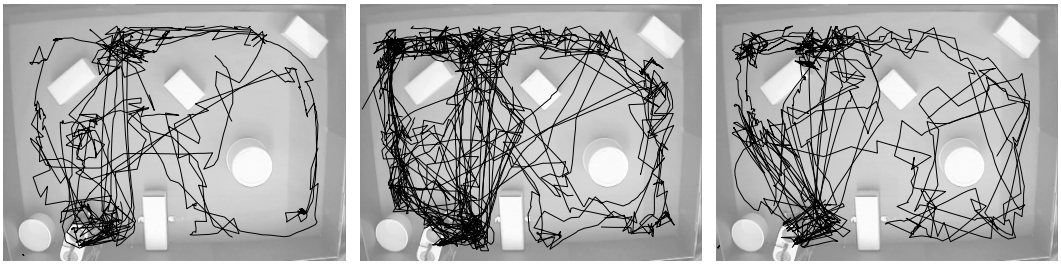
maximum signal strength and offset, calibration is performed prior to each run in order to normalize the signals.

The same three morphologies are tested as in Experiment 1. During the training period, the robot navigates with pre-wired reflexes. Infrared sensors and whisker sensors connect to a set of reflex neurons. The connections between IR sensors and reflex neurons are set to 1 for the whole training session, while the connections between whisker neurons and reflex layer are initially set to zero. During training, these connections are modified according to the DAC learning paradigm . The reflex layer is hardwired to the motor neurons that generate the motor output. Learning time is limited to 2 min to enhance the performance differences between the different morphologies. Following the training, learning is stopped, the IR sensors shut off and the robot navigates for a maximum of 3 min only using the whisker sensors. This testing phase is recorded with an overhead camera at 2 frames per second and the trajectory is extracted from the image sequence using the KLT feature tracking library [140].

Results of the Learning Experiments

To verify the prewired reflexes, 9 runs were conducted, where the robot navigates using only infrared sensors. Figure 6-7 shows that the robot is able to cover the whole area. The high concentration of lines in the upper left corner indicates that the robot spent more time in this narrow area. We can conclude that the basic reflexes are suitable for avoiding obstacles and still passing through tight spots.

In the following experiments, we test the performance of the three different robot morphologies after 2 min of learning. To evaluate the performance, we use the same measures as in Experiment 1.



(a) Morphology A (b) Morphology B (c) Morphology C

Figure 6-8: Experiment 2: Cumulated trajectories for the three morphologies A(a), B(b) and C(c).

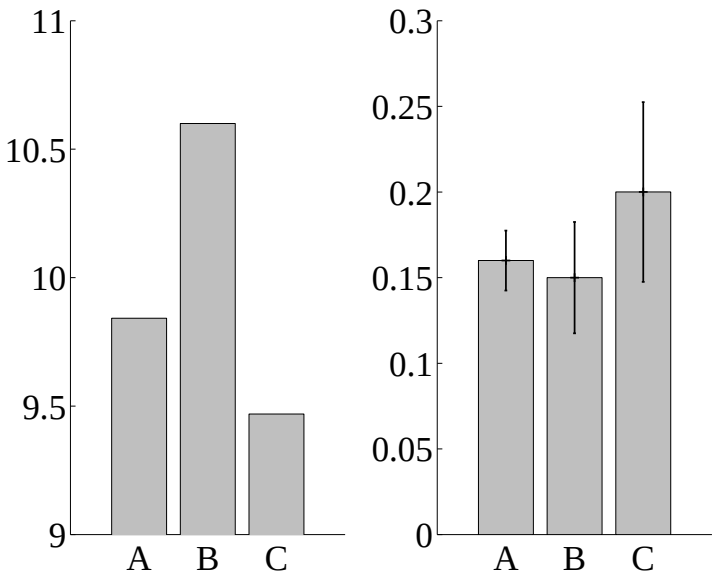
Figure 6-8 shows the cumulated trajectories of 13 runs for each morphology. Clear differences can be observed between the different morphologies. Morphology B covers much more of the available space and manages to drive around the obstacle in the upper left corner of the arena several times. Morphologies A and C hardly enter this area and get stuck more often. The high trajectory density at the entrance of this passage shows that most of the time, the robot turns on the spot instead of entering the narrow part.

To quantify the exploration of the arena, the entropy was computed analogously to Experiment 1. The computed entropies are shown in Figure 6-9(a). The highest entropy, corresponding to the most even exploration of the experimental area, is obtained using morphology B.

To quantify excessive turning, the amount of wiggling was computed as in Experiment 1. Figure 6-9(b) shows results similar Experiment 1: morphology C wiggles most, while morphologies A and B change direction less often.

6.3.3 Experiment 3: Simulation Experiments

In the previous learning experiment, we have already allowed for different relationships between activity in the whisker sensors and the obstacle avoidance behavior triggered. To investigate the interdependence between morphology and control with a continuous spectrum of whisker lengths and location, we used artificial evolution in simulation. This approach allows to co-evolve the controller and the morphology as well as investigate the influence of different whisker material properties.



(a) (b)

Figure 6-9: Experiment 2: Entropy (a) and wiggle (b) in morphologies A, B, and C.

Simulating Whisker Sensors

To simulate the deformable properties of natural whiskers, a finite element approach was followed. Each whisker consists of a chain of beam elements connected by universal damped springs (for details see [17]). The angle of bending at the point of attachment to the agent body is used for the sensory signal. With this method, two different types of whisker materials were modeled: 1) *rigid* whiskers consisting of a single beam which can only bend at its root and 2) *flexible* whiskers built up from several elements. Flexible whiskers can be bent continuously resembling more closely to natural whiskers, whereas rigid whiskers represent stiffer material often found in the construction of artificial whiskers.

Simulated Agent and Environment

The simulations are designed to match the robot experiments as closely as possible. For this purpose, a physically realistic environment is simulated based on an extended version of the Open Dynamics Engine library (ODE) [142]. This environment consists of a toroidal world (to avoid border effects) with randomly placed obstacles. The agent is modeled as a two-wheeled robot comparable to the Khepera platform with eight whisker sensors distributed symmetrically on both sides. Whiskers are equally

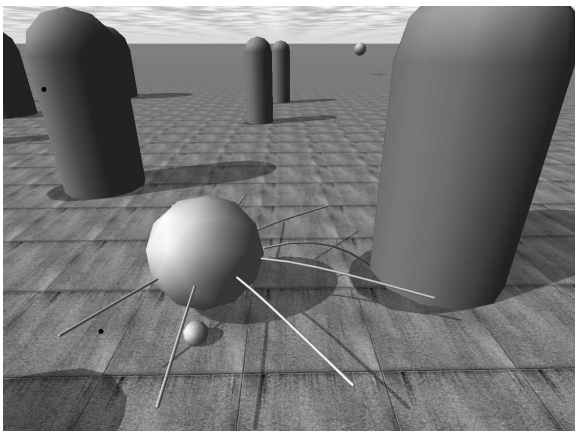


Figure 6-10: Virtual environment used for Experiment 3. The agent is shown with its left whiskers in contact with an object it has to avoid. The floating sphere close to the horizon is the target the agent is seeking.

spaced and their lengths continuously vary from the front to the back. In addition, the robot is equipped with a sensor to detect the angle to an arbitrary target. Figure 6-10 shows a screenshot of the agent in its environment.

Artificial Evolution

For an optimization of the morphology of whisker sensors, an evolutionary strategy is implemented. The task of the agent consists in approaching a target as quickly as possible and at the same time avoid contact with obstacles. It can only sense the obstacles with its whiskers. The target is initially placed at a random position, and each time the distance between target and agent falls below a given threshold distance, the target is moved to another random position.

The agent is controlled by a subsumption-like architecture [125]: when no object is detected by the whiskers, it behaves like a Braitenberg vehicle seeking for target. If an object is detected on one side, i.e. if one (or more) whisker(s) is deflected at its root more than a given threshold angle, the agent turns away for a given time period. If both sides detect some objects, the agent moves back for a given time period. All parameters controlling the target seeking and the obstacle avoidance behavior are let to evolve.

The Fitness Function

Each agent is evaluated for a fixed period of time. The fitness F of an agent is given by

$$F = a \cdot N_{\text{target}} - b \cdot N_{\text{collision}} + c \cdot N_{\text{move}} \tag{6.4}$$

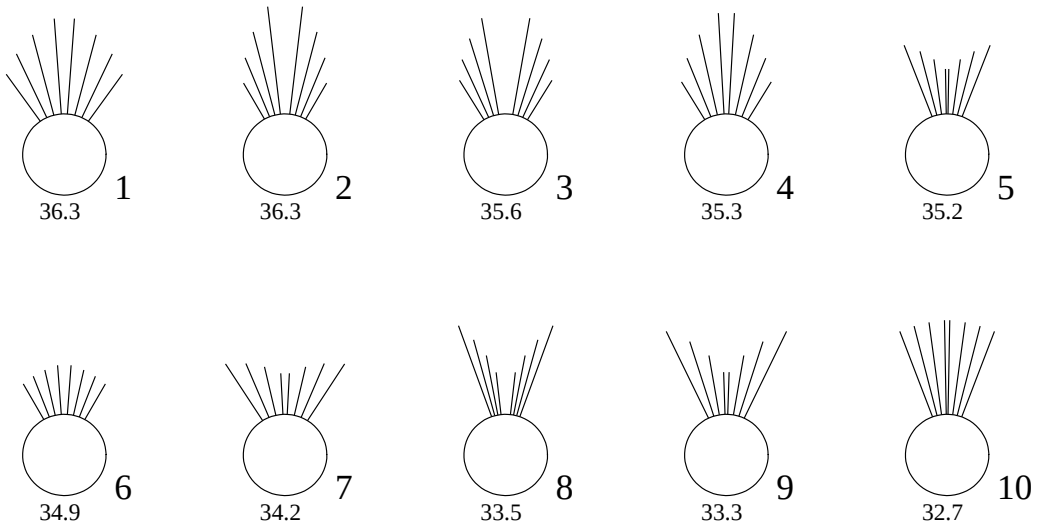
where N_{target} and $N_{\text{collision}}$ are respectively the number of targets found and the number of collisions which occurred during the evaluation period. N_{move} counts the number of different positions (with respect to a discrete grid dividing the whole space) the agent moved to. This last term is added in order to avoid solutions where the agent would simply stay in place. a, b and c are positive constants with $a \approx b \gg c$.

Results: Evolved Morphologies

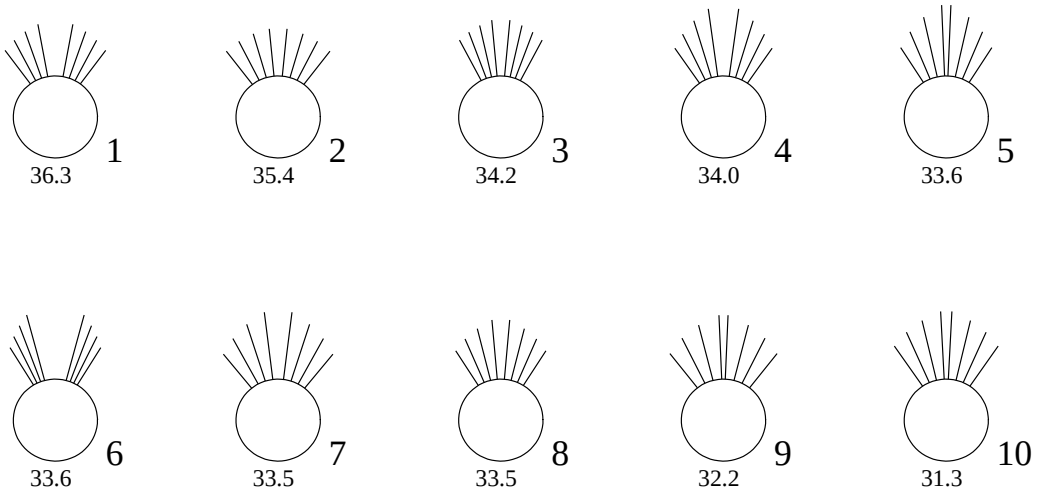
Figure 6-11(a) shows the morphologies of the fittest agents found after 10 runs of 500 generations. Different observations can be made from this. Firstly, all whiskers are systematically placed in the front of the agent rather than on its sides. This corroborates results of Experiment 1: all the evolved morphologies are variations of morphology A, where the sensory space closely matches the physical space of the agent. This is not surprising since for the given task, the agent has to avoid obstacles he might bump into, i.e. the ones detected in front of the agent. Secondly, the morphologies of the four fittest agents share a common trend: the longest whiskers are more often found in the center, with the shortest whiskers more on the borders. Note that other arrangements of whiskers were found by the artificial evolution, such as morphologies 5 and 7 in figure 6-11(a), where the whisker tips lie almost in a plane.

Rigid vs. Flexible Whiskers

The same evolution runs as presented so far were performed again, this time replacing the flexible whiskers by rigid whiskers which could only bend at their root. Figure 6-11(b) shows the morphologies of the fittest agents obtained with rigid whiskers. The comparison of figure 6-11(b) with figure 6-11(a) reveals two main differences. Firstly, rigid whiskers are found to be shorter than in the case of flexible whiskers. This difference can be explained by the fact that a small displacement of the tip of a rigid whisker produces the same deflection at the root as a larger displacement of the tip of a flexible whiskers. We also notice that artificial evolution did only find one type of morphology with rigid whiskers, namely longer whiskers in the front.



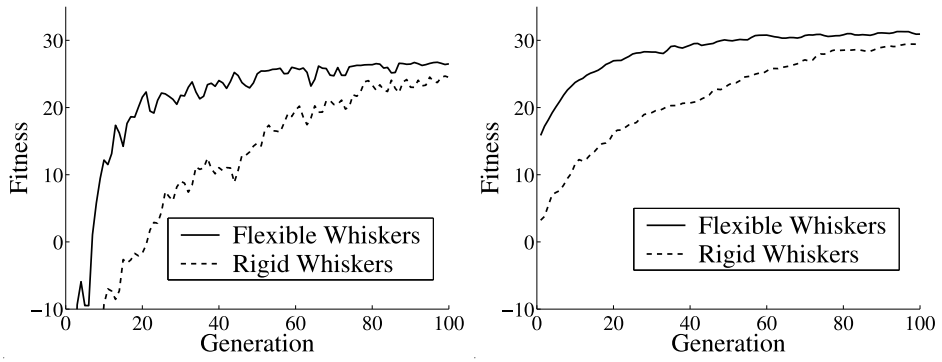
(a) Flexible whiskers



(b) Rigid whiskers

Figure 6-11: Morphologies of the best performing agents found by artificial evolution. The morphology of the fittest agent found after 500 generations is shown for each one of the 10 evolution runs.

Another significant difference between rigid and flexible whiskers can be seen at the level of the artificial evolution. Figure 6-12 shows the population fitness during the first 100 generations: the fitness increases more slowly in the case of rigid whiskers compared to the case of flexible whiskers. After the 100th generation, the fitness does not increase significantly anymore and stays at a comparable level in both case (the



(a) Population Mean (b) Best Agent

Figure 6-12: Evolution of (a) the mean population fitness and (b) the fitness of the best performing agent in the population during the first 100 generations. The values for each curve are averaged over the 10 evolution runs.

fitness in the case of rigid whiskers remains about 5% lower than in the case of flexible whiskers). One can speculate that the behavior of an agent using rigid whiskers is less robust against small changes in the parameters of the morphology and the controller: since the whiskers are less compliant, a small variation of the trajectory of the robot can produce a significant change in the sensory signals; the environment may therefore look quite different from the situated perspective of the agent, inducing possibly a drop of the agent's fitness. This could explain the discrepancy of the fitness landscape and why it is harder for the artificial evolution to find an adequate path in the genome parameter space.

6.3.4 Experiment 4: Wall-Following

Since whiskers in nature are used in different behaviors, we also evaluate the influence of morphology on a second task, where the robot has to follow a wall. We test the same three morphologies introduced in Experiments 1 and 2. The robot is placed in the proximity of a straight wall. Initially, whiskers are not in contact with the wall.

Behavioral Control

The robot is endowed with an intrinsic drive forward. If no whiskers are stimulated, the robot drives with slightly different wheel speeds. This difference makes the robot turn towards the wall. If a whisker is stimulated above threshold, the speed of the contralateral wheel is attenuated, such that stimulation in two or three whiskers will

balance the robot to drive straight. If more than 3 whiskers are stimulated, the robot drives away from the wall.

Results

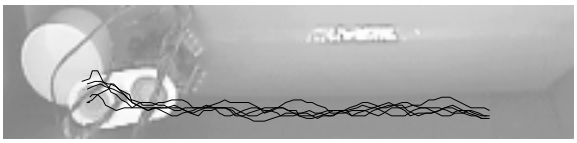
All three morphologies are able to follow the wall as observed from Figure 6-13. Nevertheless, close inspection reveals that morphology C follows the more smoothly than the two other morphologies. Figure 6-15 show the standard deviation of the trajectories of each morphology in the direction perpendicular to the wall. Morphology C performs clearly better than A and B.

An analysis of the number of whiskers touching the wall over time shows similar differences. Morphologies A and B have large variations in the number of whiskers touching. This correlates with the behavior such that especially morphology A is not able to follow the wall by stably driving parallel, but instead oscillates between smaller and larger distance to the wall. Morphology C on the other hand shows a stable activation of two or three whiskers which results in a very straight trajectory along the wall.

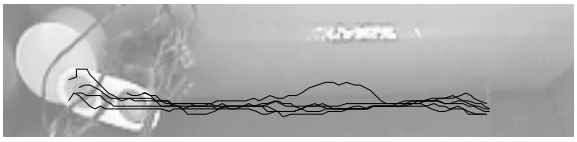
6.4 Discussion

The influence of morphology on behavior has received increasing attention during the past years. It has been recognized as a prerequisite for seemingly natural walking of humanoid robots [29, 119] and other animal robots (for example [76]). In this paper we have presented evidence for a strong relation between task and morphology in an important model system for tactile perception, namely the whisker system. For the first task – obstacle avoidance – we find both in simulation and on a robot that an appropriate morphology helps the robot to avoid obstacles and still be able to navigate its whole environment. A narrow sensory space and long frontal whiskers are found to be most successful. For a second task, wall-following, we show that again an adequate morphology leads to significantly better behavioral results. The morphology best for wall-following corresponds closely to the morphology typically found in whisker-bearing animals [21]. For both tasks, the controller was kept simple, optimization was mainly done on the sensory morphology.

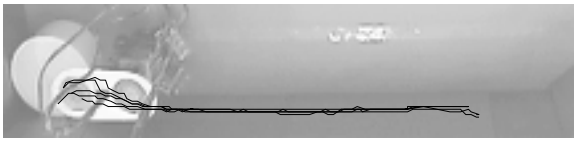
We also show the importance of the whisker material properties on the obstacle avoidance task where whiskers are used as binary touch sensors. With flexible whisker material, evolution was faster and a richer variety of morphologies was found than



(a) Morphology A



(b) Morphology B



(c) Morphology C

Figure 6-13: Qualitative results of Experiment 4: trajectories of the three morphologies following a wall. Five runs of each morphology are shown.

with rigid material. It should be noted that all evolved morphologies resemble morpholgy A in that their border whiskers barely extend over the physical dimensions of the agent body. These results support key elements of morphological computation [120, 124] by stressing the influence of morphology and material properties on sensory processing and behavior.

Our experiments serve to sharpen our understanding of how navigation based on tactile sensing can be viewed. Given that obstacle avoidance is maybe the most basic requirement for any moving system, how can we understand that the natural whisker morphology seems to be optimized more towards wall-following than towards obstacle avoidance? First it has to be stressed that these experiments were performed without visual information. Most animals have visual information which is probably very helpful for avoiding obstacles. Even animals with a wide field of view like rats have binocular vision only towards the front, but not on the sides [65]. Cats also have a nicely developed whisker system, and they have an even more frontally oriented field of view with large overlap of the two eyes [65]. Binocular vision greatly contributes to three-dimensional vision and therefore to the perception of distance. This suggests

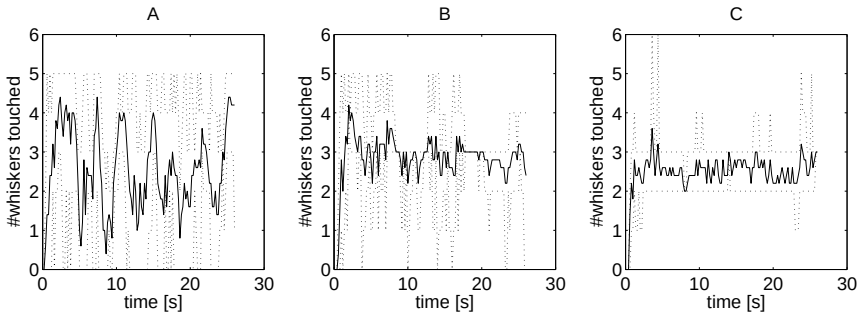


Figure 6-14: Number of whiskers touching the wall for morphologies A, B, and C (from left to right). The solid line represents the mean number of whiskers touching the wall, the dotted lines show the minimum and maximum value over 5 runs.

that as long as there is enough light, animals use vision as much as possible to avoid obstacles in the frontal direction.

The whiskers are thus especially useful laterally where they complement vision for obstacle avoidance and distance estimation. Anecdotal evidence reports that cat whiskers are just as wide as their shoulders so that they can estimate whether they will fit through an opening. Their physical and sensory space are well matched. It has been observed that cats with clipped whiskers can get stuck in tight spots. After clipping the whiskers, they are too short to yield the required information, the lateral physical space is larger than the sensory space.

If light is absent or very faint, the demands are different. The agent has to rely more heavily on tactile sensing for navigation. Our intuition strongly suggests that in complete darkness, a good strategy is to feel one's way along something rather than to walk into the open space. We automatically prefer a behavior resembling wall-following. Behavioral experiments with naturally blind mole rats have shown that in a maze task, the mole rat navigates by pressing its body along the walls. Consequently, the blind rat performs better in a maze that is just as narrow as its body, while a rat with sight performs better in a wider maze [85].

Other experiments indicate a strong interplay between the sensory spaces of different modalities. Indeed, it has been shown that animals (cats and mice) which are blinded from birth develop longer as well as stronger whiskers [127]. Our experiments also support the notion that in most animals whiskers are complementary to vision and thus optimized for tasks which cannot be as well or as easily achieved with vision only. We have shown that the natural morphology more adequate for wall-following rather than for obstacle avoidance. This suggests that the evolutionary pressure has been higher on the former behavior.

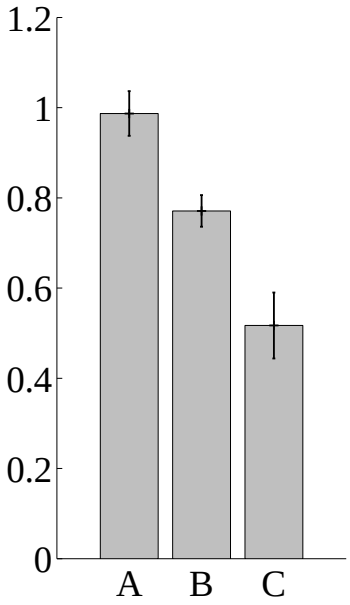


Figure 6-15: Quantitative results of Experiment 4: average deviation from a straight trajectory in morphologies A, B, and C.

We have shown that with learning, the agent is able to adjust its behavior to its sensory dimensions given proper reflexes. In our experiments, the reflexes rely on infrared sensors and hardwired connections. In a natural animal, bumping into an obstacle or getting stuck can be painful and thus triggers a strong reflex to be associated with signals from the whiskers. The animal quickly learns how much activation of the whiskers can be tolerated, and when it is better not to try to squeeze through a small hole.

Considering the interplay between task and morphology, it is worth mentioning that animals such as rats or seals can use their whiskers to discriminate textures. Such a challenging perceptual task possibly poses additional constraints on the morphology of the whiskers on the agent. Some neuroscientists argue that for texture discrimination, rats could rely on different eigenfrequencies in whiskers with different length and thickness (for review see [102, 107]). This hypothesis obviously relies on the existence of whiskers with different material properties without making any claim about their arrangement. Another hypothesis has been proposed by Brecht *et al.* [21]: they speculate that the particular arrangement found in nature is especially useful for tactile exploration of objects or surfaces because the hair tips lie in a plane. Thus, anything in front of the animal can be palpated by a maximum number of whiskers thus increasing the collected sensory information. The investigation of this hypothesis remains a future challenge for roboticists working on this fascinating topic.

6.5 Conclusion

We have demonstrated the importance of a proper arrangement of tactile whisker sensors on a mobile robot. We showed for different tasks and with a simple controller that the performance can be significantly enhanced with an appropriate morphology where the sensory space matches the physical space the agent occupies. The morphology commonly found in nature strongly resembles the morphology well-suited for wall-following. This suggests that in natural systems, the whiskers have been evolved more towards this task. The investigation of a possible interplay between morphology of different sensors and various tasks, such as the capability for texture discrimination, remains an open research question.

Chapter 7

Predicting Properties of the Rat Somatosensory System by Sparse Coding

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Neural Information Processing Letters and Reviews, Vol. 4, No. 1, pp. 11-18, ISBN 89-89453-04-6 93560

Abstract

Many studies address how neurons in the barrel cortex of rats react to stimulation of the rat's whiskers. In this study we analyse how the statistical properties of whisker deflections from typical surfaces relate to the properties of neurons in the somatosensory system. We built an artificial whisker system to record realistic natural tactile data. An artificial whisker is moved about a set of surfaces of everyday objects. We analyse how simulated neurons can represent such stimuli in an optimally sparse fashion. These representations predict a number of interesting properties of neurons in the somatosensory system that have yet to be measured.

7.1 Introduction

Whiskers provide an important source of information to rats and other rodents [149]. Rats can, for example, distinguish surface properties (texture) purely on the basis of cues from their whiskers [26, 56]. They can furthermore use their whiskers to discriminate objects [21] based on their shape. As the rat explores its environment,

its whiskers are moved over surfaces of various shape and texture. Neurons in the sensorimotor system thus need to transmit the relevant information to subsequent brain areas. The whisker deflections caused by these stimulations define the input to the rat's somatosensory system. Although a large number of studies analyse the electrophysiological properties of the barrel cortex [2, 104, 110], the relevant features of its input that should be transmitted by neurons have remained unknown.

Recent studies show a growing interest in the texture discrimination abilities of rats (for a review see [102]). Frequencies induced in the vibrissa hair are discussed as the relevant information used for this behaviour [63, 113]. Furthermore, it was shown that for an artificial whisker sensor, different textures could be discriminated analytically using power spectra [47].

In an emerging branch of neuroscience, optimal coding of natural scenes, it is studied in what respect neurons optimally encode natural stimuli. As animals grow up and evolve in a world of approximately constant properties, the properties of the brain should be well matched to the properties of the world [12]. Within this field, many studies address the properties of natural stimuli in the visual domain addressing the scaling behaviour of natural images [131] or the properties of higher order statistics using sparse coding [117, 118, 146]. Theses studies showed that many properties of the visual cortex can be understood as sparsely encoding the stimuli it typically encounters. A number of studies also address sparse coding in the auditory domain addressing the auditory nerve [94] or the primary auditory cortex [89]. Again these studies showed that many properties of the auditory system can be understood as sparsely encoding natural sounds.

Optimally sparse in these studies means that the neurons often have an activity close to zero and then sometimes have very high activity. Drawing upon this inspiration, we analyse the somatosensory system with similar methods. Sparseness has two distinct albeit related meanings: (1) At any point of time only a small number of neurons should be active (sparseness over the population). (2) Over the course of time each neuron should be active only rarely (sparseness over time). While the early explorations of sparseness often used definition 1, most modern studies use definition 2 as the implementation is typically a lot faster and in many cases the results are identical. There are a large number of discussed reasons why sparseness should be useful. Just to name two of them: (1) Sparseness ensures that information is transmitted using a minimal number of spikes emitted by the neurons and therefore results in a minimal energy consumption of the brain. (2) Sparse representations also maximise the independence between neural outputs and thus make recognition tasks easier for

subsequent stages of cortical processing.

In this paper, we examine the statistics of natural stimuli to the somatosensory system. We thus examine if not only visual and auditory but also somatosensory stimuli can be understood as sparsely encoding typical stimuli. In analogy to the databases of natural images used for visual studies, we first need a database of natural whisker deflections. We thus built an artificial whisker system with a real rat whisker attached to a capacitor microphone. This set-up was described in previous papers [60, 98]. This extends previous robotics studies that used simple whisking devices measuring distances or contact only [79, 80, 133], but do not capture the rich information picked up by natural whiskers in a biologically plausible way. We collect whisker data by actively moving the whisker over a set of complex stimuli. The motion pattern of the whisker in this configuration closely matches the motion patterns of the whiskers in natural conditions (rough visual observation) and has similar movement frequency and the same shape.

We analyse if the neurons in the vibrissal system can be understood in terms of leading to sparse activity in response to these natural inputs. We represent the data coming from our artificial whisker system in the spectro-temporal domain to allow for a large class of spectrotemporal responses. Simulated neurons optimally coding for these data are analysed and generate predictions about neurons in the somatosensory system.

7.2 Hardware Design and Methods

This section describes the artificial whisker system we built and the responses we recorded in response to moving the whisker over natural surfaces. The desired artificial whisker should be functionally comparable to a natural rat whisker and therefore be sensitive to small amplitude deflections and fast oscillations. We investigated different designs, including piezo-electric crystals and small capacitor microphones. The influence of different whisker materials (metal wire, polyvinyl, human hair, rat whiskers) has also been compared [98]. Rat whiskers respond to a range of spatial frequencies and showed little oscillations. The most promising results were gained with a combination of the rat whisker with a capacitor microphone technique, which is described in the following subsection.

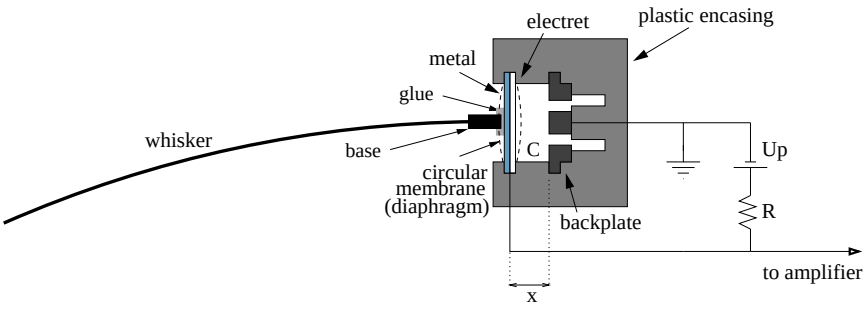


Figure 7-1: Basic schematic of the artificial whisker with an electret microphone picking up the oscillations and converting them into electrically measurable signals. The whisker is glued onto the membrane of the microphone. The deflection of the membrane is measured by the change of capacitance. The related change of voltage is fed into a preamplifier circuit.

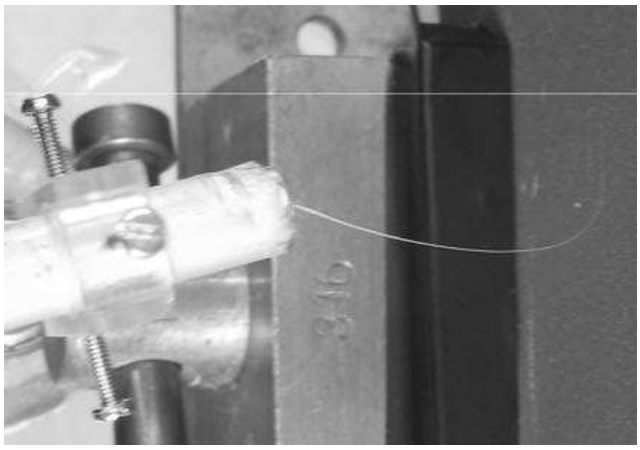


Figure 7-2: Image of the artificial whisker system used for recording the data.

7.2.1 The Artificial Whisker System

We attached a rat whisker to the diaphragm of a capacitor microphone using cyanoacrylic super-glue. Vibrations and displacement of the hair results in deformations of the microphone membrane. The resulting change in voltage is pre-amplified and digitally recorded. This technique allows us to measure fast oscillations of the whisker even if the amplitude is very low. The microphone with the rat whisker is attached to a servo motor to produce active whisking in a controlled way as described in the next section. A schematic drawing of the device is shown in figure 7-1, a picture of the artificial whisker system can be seen in figure 7-2.

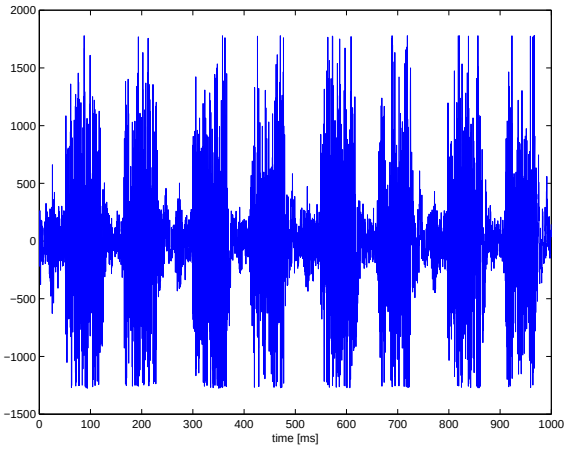


Figure 7-3: Capacitance trace measured by the artificial whisker system while whisking back and forth over an object.

7.2.2 The Deflections of the Artificial Whisker

We recorded deflections from a single whisker being automatically swept over different objects (sandpaper, leather, wool, etc.) with a servo motor turning back and forth at frequencies of either 1 Hz or 4 Hz. While this is a slow movement it is of the same order of magnitude as natural whisking of rats which is at about 8 Hz. Capacitance readings are sampled at 4000 Hz. In contrast to a previous study [60], the stimulation of the whisker was modelled on the active whisking behaviour of rats and mice. Previously, data was acquired either by manually sweeping the sensor across different surfaces or by stimulating the whisker by a rotating drum covered with sandpaper of varying roughness. In the first case, small variations in distance and speed could not be controlled and the whisker was not tilted as in natural whisking. The latter stimulation does not correspond to the biological reality and results in continuous, uniform stimulation. As some electrophysiological findings about differing responses in the whisker processing pathway suggest, this distinction might be highly relevant [143]. A typical trace of capacitance of the artificial whisker system can be seen in figure 7-3. It has eight signal peaks per second because of the forth and back movement.

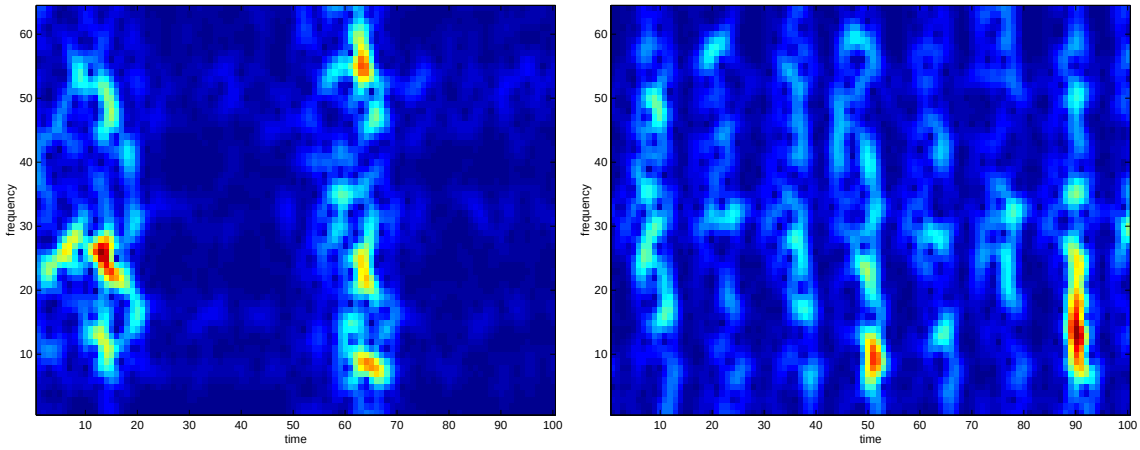


Figure 7-4: Sample spectrogram of whisker data (left: 1 Hz data, right: 4 Hz data). The frequency axis ranges from 1 Hz to 512 Hz while time runs from 0 to 1000 ms in steps of 10 ms. The colour codes for the intensity, red for high values and blue for low ones.

7.3 Results

7.3.1 Representation in Spectrogram Space

Time varying data are conveniently analysed in spectrogram space, the space spanned by frequency and time. In this space both changes over time and over frequency are easily understood. This representation is particularly useful for the whisker system since rats are able to discriminate surfaces of different spatial frequencies [26]. It has also been shown analytically that the whisker oscillation frequencies elicited by different textures can be used to discriminate between different surfaces [47]. We thus present the input signals as spectrograms. The resolution on the tonotopic axis is 64 points, covering a frequency range from 1 to 512 Hz. In figure 7-4, three typical samples of such transformed whisker data can be seen. These spectrograms show that whisker deflections lead to a largely conserved frequency-time response.

7.3.2 Principal Component Analysis

Neurons usually represent the properties of stimuli over a localised window of time. To analyse the properties of these stimuli we cut the spectrogram data in windows of 250 ms each, overlapping by 100 ms. The temporal resolution of these windows is 25 points. We subsequently assemble a set of 24360 samples of data spectrograms from a recording time of about 4 minutes.

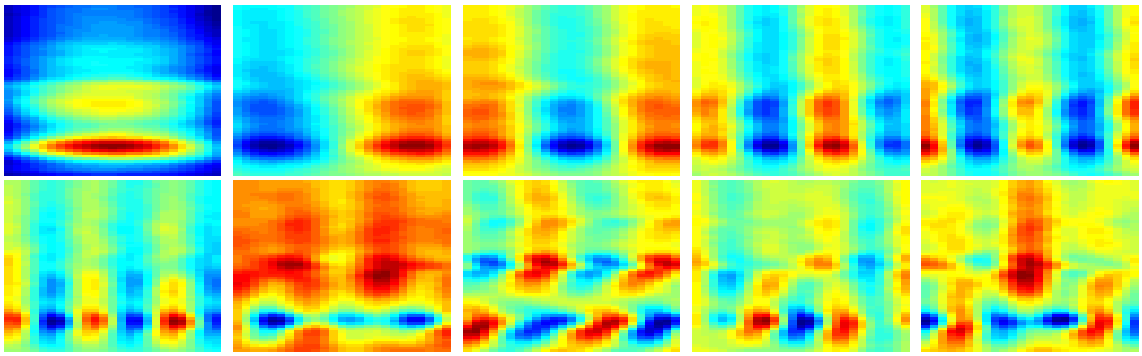


Figure 7-5: First 10 principal components of the spectrogram data. The PCA is applied to the whisker data in spectrogram space, using windows of 250 ms.

For the learning studies, the spectrograms are first compressed by a principal component analysis (PCA) using the first $n_{PCA} = 100$ principal components (out of $25 \times 64 = 1600$). These components capture more than 96% of the variance. In Figure 7-5, the first 10 principal components of the spectrogram data are shown, sorted by the size of their corresponding Eigenvalues. The purpose of the PCA is merely the compression of the data. It does not significantly influence the results of the sparse coding described in the following subsection.

7.3.3 Sparse Coding and ICA

A set of 32 simulated neurons is trained to optimally code for the recorded dataset. The activity of the neurons is calculated as

$$A_i(t) = I(t)W_i(t),$$

where A_i is the activity of the neuron, W_i is the weight vector of the neuron i. $I(t)$ is the input vector of length $n_{PCA} = 100$ shared by all neurons. This input vector itself again contains a representation of time as it encodes the whole spectrotemporal window. The weight vector of each neuron is optimised by scaled gradient descent to minimise the following loss function:

$$\Psi_{total} = \Psi_{cauchy} + \Psi_{std} + \Psi_{decorr} \quad \text{, with:}$$

- Cauchy: $\Psi_{cauchy} = \frac{1}{n} \sum_i < \ln(1 + A_i(t)^2) >_t$,
  with $< \cdot >_t$ being the average over time t

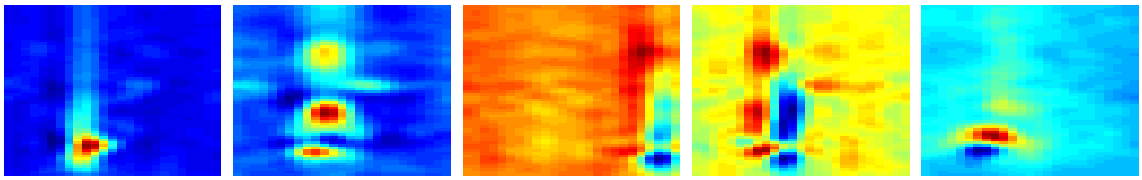


Figure 7-6: Five typical samples of colour-coded spectrotemporal receptive fields out of 32 neurons. y-axis: frequency (1 Hz to 512 Hz), x-axis: time (0 to 250 ms).

- Standard deviation: $\Psi_{std} = \frac{1}{n}\sum_i(\sigma_{A_i} - 1)^2$
- Decorrelation: $\Psi_{decorr} = \frac{10\sum_{i,j} C_{ij}^2}{(n-2)(n-1)}$,
  with $C = cov(A)$ being the $n \times n$ covariance matrix of A

Ψ_{cauchy} is a function that favours sparse representations. The two other loss functions ensure the standard criterion used in Independent Component Analysis (ICA) and sparse coding studies that the output variances should be unitary and the output covariances should be vanishing. It can be shown (see [88]) that the decorrelation term is equivalent to minimising the reconstruction error for the original dataset, given a linear system and an overcomplete set of neurons.

7.3.4 Spectrotemporal Receptive Fields

Simulated neurons are optimised to sparsely encode naturally occurring whisker deflections. Figure 7-6 shows the general properties of the resulting spectrotemporal receptive fields. Out of 32 receptive fields, 18 are similar to plot A, 6 are similar to plot B, and there are some receptive fields looking like C, D, and E. Since Ψ_{cauchy} is symmetric, the receptive fields can have positive or negative localisation features. Most of the analysed neurons are localised in time and frequency.

To further quantify this property, we introduce two measures of localisedness (figure 7-7). For the analysis, we calculate the average energy over time, and the frequency for each receptive field, respectively. We also measure the width of the maximum peak at half the peak value for time localisation, and the octaves $log(f_l/f_h)$ for frequency localisation. More than 96% of the receptive fields have a localisation measure in time of less than 80 ms. This seems to be necessary for texture discrimination. Arabzadeh et al. [9] report that rats can distinguish textures already after an offset of $5-15$ msec after stimulus onset. The receptive fields have a tuning width in frequency of less than one octave in 81% of the neurons. The cells coding for the data

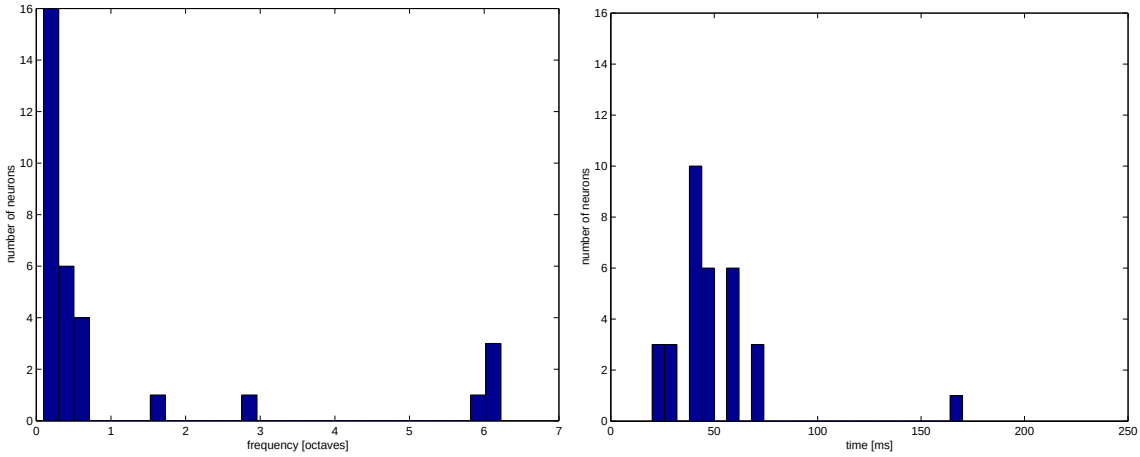


Figure 7-7: Histograms showing the localisedness of the spatiotemporal receptive fields for frequency in octaves (left figure) and for time in ms (right figure). The number of examined receptive fields is 32.

recorded for this research show significantly higher localisedness than cells coding for the sandpaper data (see [60]).

This is in analogy to sparse simulated neurons in the visual system that obtain localised receptive fields in space and orientation [118]. In addition to this, they are often tuned to changes or even modulations of the energy of the input over time, such as C and D in figure 7-6. This property might be useful for tactile texture recognition. We predict that in a similar setup for electrophysiological measurements, the somatosensory neurons should be tuned to both energy and frequency.

7.4 Discussion

We predicted properties of cells as they might be found in the somatosensory system of a rat by simulating neurons that receive input from an artificial whisker system and optimising their properties so that they exhibit optimally sparse response patterns.

There are two major assumptions that have to be considered: One is the choice of the preprocessing of the data. We decided to use spectrograms since data received from whiskers have very similar properties to auditory data with regards to their dimensionality and structure. It thus is likely that similar analysis methods should be used. It is up to date not known, what preprocessing is performed on the information travelling from the whisker follicle in rats to the barrel cortex. The other assumption is that the natural input is not assigned a class by any means of supervised learning,

the clustering happens completely unsupervised on input data varying in material, speed of movement, frequencies, etc.

Our study shows that a pressure for sparse coding together with the chosen preprocessing would results in neurons that are typically localised both in time and in frequency. Modulations in time has been shown for neurons in the barrel cortex: A recent study by Arabzadeh et al. [9] has investigated neurons in the barrel cortex of rats and found no specifity for specific frequencies, but an encoding of the product of frequency and amplitude of the whisker movement. This seems to be in contradiction to our results, however, there are major differences between the two studies. The experiments described in [9] have been performed on anaesthetised rats without active whisking. Our experiments use active whisking frequencies of 1 or 4 Hz. Their stimulus to the whisker is a very controlled signal consisting of a single frequency presented as a sine wave each, we are presenting the whisker system with natural stimuli consisting of a whole range of frequencies. It is therefore impossible to directly compare the results, but further experiments are needed to elucidate the way by which the brain combines signals at different frequencies.

7.5 Future Work

The research described in this paper results in properties of simulated cells coding for natural whisker stimuli. In a next step, we will perform behavioural experiments on an artificial mouse robot. One of the advantages to use sparse coding in a robotic setup is the task independence of the sensory modality. Sparse models for the visual domain have already been applied successfully to biologically inspired sensorimotor tasks [160]. The receptive fields of the simulated neurons from our studies will be used to learn to discriminate different objects and textures. This will be based on the activation of a small number of neurons which are optimally tuned to the nature of the stimuli instead of using the original raw signal.

Chapter 8

An Active Artificial Whisker Array for Texture Discrimination

Miriam Fend, Simon Bovet, Hiroshi Yokoi and Rolf Pfeifer

Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Las Vegas, October 2003, Vol. II, pages 1044-1049

Abstract

Whiskers are powerful sensors for robots that are not only useful for basic tasks such as obstacle avoidance, but also have the potential for gathering rich information about objects. We have developed an active multi-whisker array modelled on the rat whisker system which can be mounted on a mobile robot. We show that with this whisker array we can discriminate different textures based on the frequencies they elicit in the whiskers. We exploit the phase-locked structure of our data using sensory-motor integration. The data were generated by periodic active movement of the whiskers. Two factors enable better discrimination of the textures: firstly, considering several touch events from one whisker and secondly, combining the information from more than one whisker.

8.1 Introduction

Many different animals use whiskers as an important sensory modality. In mammals, they are useful for many different tasks: Rats can navigate in darkness without col-

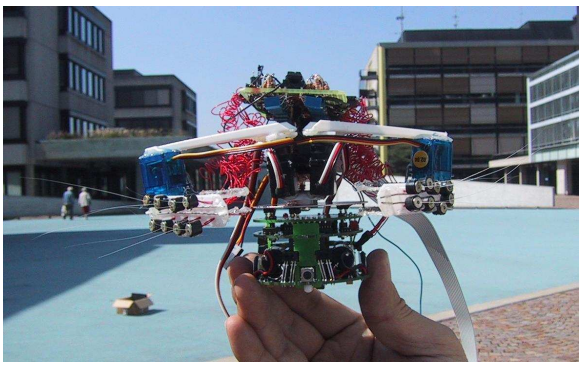


Figure 8-1: Picture of a Khepera robot with two active whisker arrays. This robot might be used in future experiments.

liding with obstacles [149], and they are able to discriminate between different shapes [21] and surface structures [26, 56]. Seals can hunt fish in murky water by detecting the turbulences generated by prey with their whiskers [36]. Their importance for the animal can also be deduced from the neuroanatomy found in rats, where a prominent part of the somatosensory cortex, the barrel cortex, is devoted to processing the whisker signals, and has a beautifully preserved topology of the precisely arranged whiskers [159].

Although whiskers are such an important tactile sensor for very different animal species, roboticists have not yet studied them in great detail. So far, they have mainly been used as binary touch [164] or as strain sensors [80, 150, 158]. Their use for fast obstacle avoidance of a robot has been shown within an engineering approach [79]. Moreover, whiskers have great potential for robotic applications, as they do not involve heavy contact with objects [150, 158] and are independent of illumination. Development of tactile sensors has largely aimed at mimicking the skin sensors humans and primates have in their finger tips [77].

While other sensory modalities such as vision already provide a lot of information that can be analyzed statically, a touch sensor usually needs to gather information over time. This can be done either in an active way by moving the sensor over a surface [141], or passively, when the object is moved over the sensor. The necessity for active sensing can easily be made plausible: With a fingertip placed lightly on a surface without any movement across, it is very difficult to discriminate different textures. The task becomes fairly easy for us, when we start to move the finger across the surface. This example shows how tactile exploration can be facilitated by active movement. In fact, rats and mice move their whiskers actively back and forth [156] with about 8 Hz when exploring objects [26]. As they whisk, their whiskers move

synchronously most of the time [135].

Since whiskers are such powerful tactile sensors that are extremely useful in faint light or darkness, we constructed an active multi-whisker array. We recorded the whisker signals while actively moving the whiskers across different textures and analyzed the resulting signals using frequency analysis. With this active process, we can use sensory-motor integration to structure our input data (for review see [125]). Using multiple whiskers, we can discriminate more textures of different roughness than with only one single active whisker. In future work, we will use this powerful sensor on a mobile robot (figure 8-1) for navigation and exploration of the environment.

8.2 Construction of the Active Whisker Array

The whisker sensor we used consisted of an capacitor microphone with a natural rat whisker attached to it [98]. Physical force on the whisker hair deforms the microphone membrane and results in a voltage signal different from the resting state. This signal from the microphones is amplified on the robot and transmitted via cable to a host computer equipped with a data acquisition card.

One whisker array consists of 8 whiskers, which are arranged in two rows of four whiskers. Active movement is along one dimension, using a small servo motor (Graupner, DS281). The microphones are held by plastic supports embedded in a slightly flexible membrane. Rotation of the motor moves and bends the membrane causing the microphones to tilt (figure 8-3). The whisker therefore sweeps mainly with its tip, while the base does not translate much (figure 8-2). This construction made a fairly large translation of the whisker tip possible, while the mechanical construction remains compact. Another advantage is that the bases of all whiskers within the array have a constant distance to the object while actively whisking. The angular movement achieved by our device was about 40°. The motion generated with this active whisker array is quite similar to the whisking movement performed by rats. Rats move their whiskers mainly in one dimension and all whiskers on one side of the head move mostly in synchrony [135].

The servo motor can be controlled from the computer via a Hitachi microchip (H8tiny/3664F). The whisking frequency was approximately 0.7 Hz, but the motor is able to move much faster. Data acquisition was done with a A/D card sampling 12 bits at 11250 Hz per channel. Parallel to the data acquisition, the motor commands were recorded. This allows us to allocate the direction of movement to the data acquired.

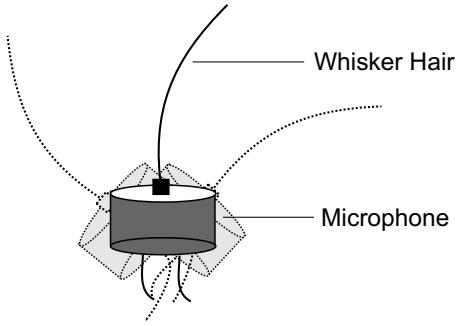


Figure 8-2: Scheme of the movement of the whisker on the microphone, when tilted at the base. In light gray, the end positions of the whisker sensor can be seen.

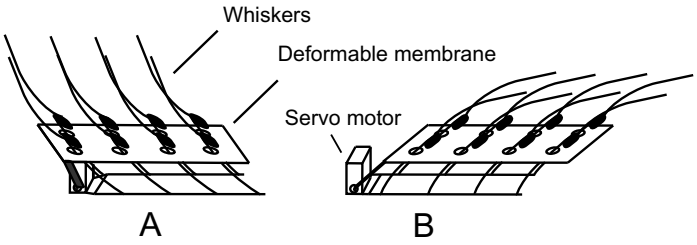


Figure 8-3: Schematic drawing of the active whisker array. Movement of the motor moves the membrane and thus the base of the microphone. This movement causes the microphone to tilt. The sweep of the whisker tip is therefore much larger than the translation of the base. Forward movement is defined as transition from B to A.

8.3 Texture Analysis and Discrimination

During the experiment, we used 11 different textures (see table 8.3). As reference, the actively moving whiskers were also recorded without touching anything. Since the data consist of time signals (figure 8-4), it is reasonable to start by considering a frequency analysis. From the spectrograms (some examples are shown in figure 8-5) we could see that there is no characteristic temporal structure. We therefore only considered the power spectral densities of the touch event as a whole. In order to compare two signals recorded with different textures, we define a "distance" in a straightforward way by comparing their frequency spectrum.

For each set $S = \{T, W, D\}$ of texture $T \in \{0, 1, \ldots, 11\}$, whisker $W \in \{1, \ldots, 8\}$, and movement direction $D \in \{\text{forward}, \text{backward}\}$, we define a "signature"

$$\sigma^S(\omega) :=< \frac{1}{N_T} \sum_{n=1}^{N_T} p_n^S(\omega) > \tag{8.1}$$

where $p_n^S(\omega)$ denotes the power density at frequency ω of the n-th stroke event, and

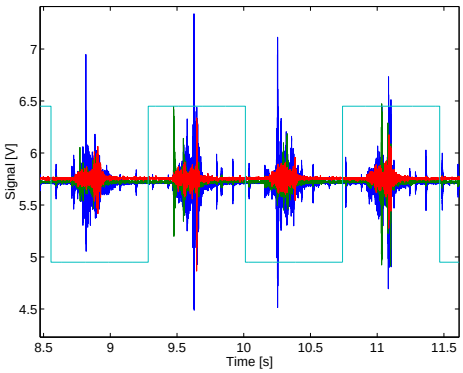


Figure 8-4: Raw time signals for the whiskers. The square signal indicates the motor command.

Number	Texture
0	None
1	Sand-paper grain 60
2	Sand-paper grain 80
3	Sand-paper grain 120
4	Sand-paper grain 180
5	Sand-paper grain 240
6	Sand-paper grain 400
7	Sand-paper grain 600
8	Foam mouse-pad (recto)
9	Foam mouse-pad (verso)
10	Carpet
11	Metal

Table 8.1: Textures used in the experiment.

N_T the number of touch events. $< \cdot >$ is a low-pass filter consisting of a convolution with a Blackman window. A window of 70 Hz was used in this study.

In other words, signatures are power density spectra: we divide the raw time signal (as shown in figure 8-4) in several chunks corresponding to the stroke events in one given direction. We then calculate for each chunk the power density spectrum with a FFT, take the average over the N_T touch events, and eventually smooth the resulting spectrum. Examples of signatures are shown in figure 8-6.

We can now define a distance between two signatures σ_1 and σ_2:

$$d(\sigma_1, \sigma_2) := \sqrt{\int_{\omega_{\min}}^{\omega_{\max}} d\omega \left(\tilde{\sigma}_1(w) - \tilde{\sigma}_2(w) \right)^2} \tag{8.2}$$

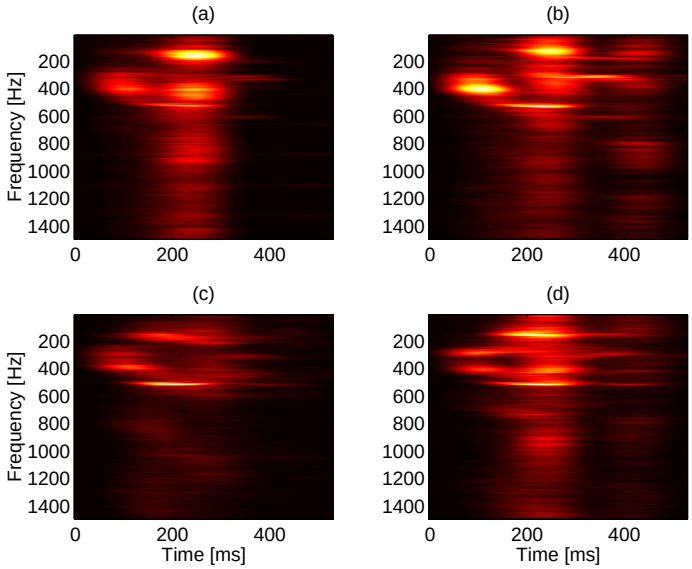


Figure 8-5: Spectrograms of the time signal recorded from one whisker moving in one direction over different textures. a) Texture 2, b) Texture 5, c) Texture 8, d) Texture 9 (see table 8.3).

The signatures are normalized to have the same total power: $\tilde{\sigma}(\omega) := \frac{1}{P}\sigma(\omega)$, $P = \int_{\omega_{\min}}^{\omega_{\max}} d\omega\, \sigma(\omega)$[1]. Thus the distance measures the discrepancy of two signatures by calculating the euclidian distance between the two curves of the corresponding power density spectrum.

A set of textures $\{T_k \mid k = 1, \ldots, N_K\}$ is said to be discriminable by one whisker W in one direction D if newly collected signatures σ_{test} (arbitrarily called tests) can be assigned correctly to previous signatures σ_{ref} (called references), and conversely. In our case, this means $\forall\, l \neq k \in \{1, \ldots, N_K\}$ that

$$d(\sigma_{\text{test}}^{S_k}, \sigma_{\text{ref}}^{S_k}) < \min\{d(\sigma_{\text{test}}^{S_k}, \sigma_{\text{ref}}^{S_l}), d(\sigma_{\text{ref}}^{S_k}, \sigma_{\text{test}}^{S_l})\} \tag{8.3}$$

where $S_k = \{T_k, W, D\}$. When considering more than one whisker, we simply add the distances calculated for each whisker: for a set of whiskers $\{W_w \mid w = 1, \ldots, N_W\}$, equation (8.3) becomes:

[1]Since we have discrete data, integrals are replaced by sums for actual calculations.

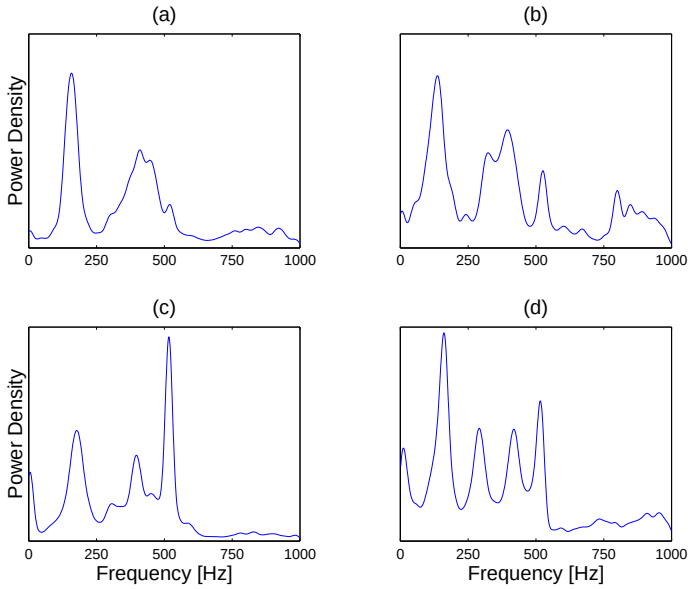


Figure 8-6: Power spectral density plots (signatures) corresponding to the textures and conditions used in figure 8-5.

$$\sum_{w=1}^{N_W} d(\sigma_{\text{test}}^{S_k^w}, \sigma_{\text{ref}}^{S_k^w}) < \min \left\{ \sum_{w=1}^{N_W} d(\sigma_{\text{test}}^{S_k^w}, \sigma_{\text{ref}}^{S_l^w}), \sum_{w=1}^{N_W} d(\sigma_{\text{ref}}^{S_k^w}, \sigma_{\text{test}}^{S_l^w}) \right\} \tag{8.4}$$

where $S_k^w = \{T_k, W_w, D\}$.

Figures 8-7(a) and 8-7(b) show the average number of discriminable textures as a function of the number of touch events N_T used for the signatures (equation 8.1) and the number of whiskers N_W used for the discrimination (equation 8.4). The average is take over all possible sets of discriminable textures and all combinations of N_W different whiskers.

8.4 Results and Discussion

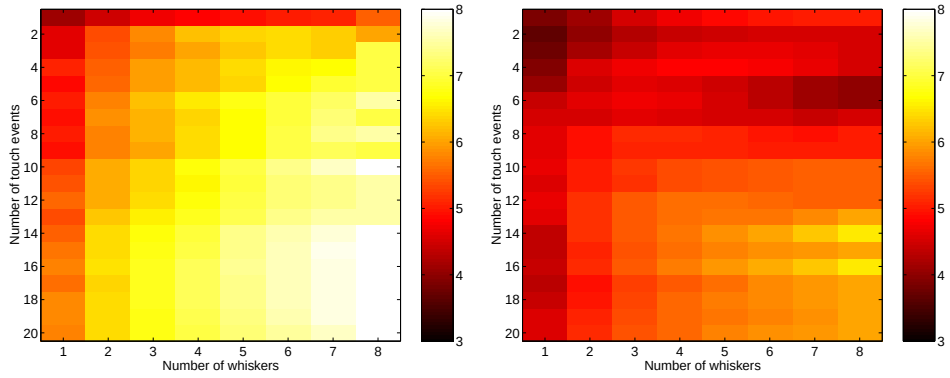
The aim of this study was to build an active whisker array capable of discriminating textures. Reference and test data were collected independently for all textures. Signatures were then calculated with up to 20 touch events for frequencies ranging from $\omega_{\min} = 0$ to $\omega_{\max} = 1000\,\text{Hz}$ (we observed so far that there were no significant signal at higher frequencies, see figure 8-5). Differences between textures can already

be seen in the signatures (figure 8-6).

Figure 8-7(a) shows the average number of textures that can be discriminated as a function of the number of touch events (along ordinate) considered for calculating the signatures and the number of whiskers (along abscissa) combined for the discrimination. This figure shows that increasing any of these two factors mostly leads to a better discrimination. Higher resolution of textures can be achieved by increasing both the number of touch events and the number of whiskers considered.

In order to test the importance of sensory-motor integration, we calculated again the number of discriminable textures but this time, the raw time signals were divided into chunks of an arbitrary length of 1 second, irrespective of the motor command signal. Results are shown in figure 8-7(b). One reason why discrimination is this time poorer is the fact that forward and backward movements of the whiskers elicit different frequency components. It is therefore important for our system to phase-lock the whisker signals using a motor feedback.

The natural rat whiskers we used have several interesting properties. Not only are they almost critically dampened, they also have a preferred direction which is shown schematically in figures 8-2 and 8-3. This directionality elicits differences in the data between forward and backward movement (data not shown). It is therefore crucial for our analysis that we can allocate forward and backward movements by recording the end position of the motor during each cycle. This produces phase-locked data,



(a) (b)

Figure 8-7: Average number of discriminable textures as a function of the number of touch events and the number of whiskers considered. (a) Phase-locked data. In this case, the average number of discriminable textures is approximately a monotonically increasing function of both parameters. (b) Motor signal ignored. Discrimination capabilities decrease compared to the phase-locked data.

just as in natural systems such as rats.

These results suggest that there are several properties in the whisker system that contribute to make it such a powerful tactile sensor. Firstly, we have shown that the whisker hairs are capable of transducing some properties of different materials as frequencies. It is not known so far, how these frequencies could be recorded by the animal as they do not have a specialized structure which anatomically resolves the whisker frequencies, as the cochlea does for sound waves. This remains an intriguing question for biologists.

Secondly, the integration of sensory and motor data proved to help structuring the data such that discrimination of textures was possible. There is some evidence from biology that rats also use phase-locking in processing the whisker signals in the primary somatosensory cortex (for review see [2, 3]) and that there is a close connection between motor cortex and the somatosensory cortex [86]. Our results show that at least in this artificial system, phase-locking helps to interpret the complex whisker signals.

A third characteristic of our experimental system is that we use several whiskers at the same time. This multi-whisker array includes a certain amount of redundancy, as 1) the whiskers are similar, but not identical, 2) neighboring whiskers move over partially overlapping surface areas. Since the whiskers have different physical properties (such as length, thickness and shape), they may have different qualities in resolving textures. Possibly, the longer, thicker hairs detect different features of surfaces than the thinner, shorter whiskers. Additionally, the fact that they partially touch the very same surface makes their signals comparable, but at the same time adds some information about a larger area. For this study we used homogenous textures, but with refined sensory-motor integration, it might be possible to also discriminate inhomogeneous textures or different areas on one surface. Using many whiskers also provides several touch events with only one stroke, so it is probably very useful for speeding up the discrimination by providing more input data.

Finally, it is striking that already the straightforward comparison of the whisker data presented in this paper revealed differences between textures. This opens up the question, whether it is due to intrinsic properties of the natural whiskers. This is also suggested by the comparison of natural rat whiskers with different artificial whisker materials and natural non-whisker hair in [98]. Possibly, the ones transducing relevant physical properties of surfaces were selected during the course of evolution. A detailed analysis of the material properties of rat whiskers, as well as a more refined analysis of the recorded data, might shed light on this intriguing question.

8.5 Conclusion and Future Work

In this study we have shown that we can use an active multi-whisker sensor to discriminate different textures based on their power density spectrum. For this we have structured the sensory data based on the motor commands. We think that this will be a very useful sensor for many robots. It complements vision as it is independent of light and capable of detailed information of objects at hand.

In the future, we will perform a more refined analysis of the whisker data in order to better understand what characteristics of the data are relevant. We will also conduct navigation and learning experiments with mobile robots and active whisking.

Finally, we would like to investigate the combination of whisker sensors with other modalities such as camera vision in the context of mobile robot behavior and cross-modal learning.

Chapter 9

Whisker-Based Texture Discrimination on a Mobile Robot

Miriam Fend

Proceedings of the 8th European Conference on Artificial Life (ECAL), Lecture Notes in Computer Science 3630, pages 302-311[1]

Abstract

Sensing in the dark is a useful but challenging task both for biological agents and robots. Rats and mice use whiskers for the active exploration of their environment. We have built a robot equipped with two active whisker arrays and tested whether they can provide reliable texture information. While it is relatively easy to classify data recorded at a specified distance and angle to the object, it is more challenging to achieve texture discrimination on a mobile robot. We used a standard neural network classifier to show that it is in principle possible to discriminate textures using whisker sensors even under real-world conditions.

9.1 Introduction

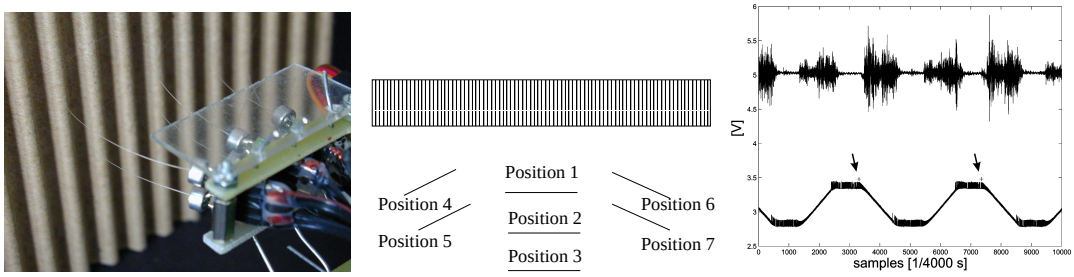
When light is dim or fading, tactile information becomes more and more important. In nature, many night-active animals such as rodents, cats or oppossums have developed an exquisite tactile organ, the whiskers. With their large mystacial whiskers, rats for example not only navigate to avoid obstacles, but they are also able to discriminate different textures and shapes [21]. Behavioral studies in rats have shown that their

ability to discriminate surface structures with the whiskers is comparable to ours using our fingertips [56] [26]. Unravelling the information coding in the rat whisker system has recently attracted different researchers both from biology [107] [102] [9] [8] and from the field of robotics [48] [138] [157] [132] [82]. Theoretical studies have analyzed the properties of whisker vibrations [98] [47] [67] and their implications on neural coding and learning of simulated receptive fields [60] [59].

So far, tactile stimuli have largely been acquired by keeping parameters such as distance and orientation of the whiskers constant with respect to the texture (as in [138] [47]). Although it is reasonable to assume that animals can position their head appropriately, they are also able to discriminate textures from far away when forced to do so. One of the main differences between analyzing recorded data and using a behaving robot is that different parameters such as distance and angle towards the texture are not necessarily well defined. Thus, it is important to record data with different parameters and identify features significant for the discrimination of textures. Such features are necessary for the construction of a behaving system capable of showing discriminatory behavior comparable to a trained rat.

To our knowledge, so far only one study has conducted experiments on texture discrimination with a mobile robot [138]. In their experiment, the robot showed a wall following behavior stimulating the whisker sensors by moving them across the wall. When a texture was encountered, the robot learned to avoid the wall based on the activity pattern of its neural network. Following the wall not only generates input, it also controls for the distance and angle at which a tactile pattern is sensed. The input to the neural system is thus more reliable and reproducible than at random orientations.

In the series of experiments presented in this paper, we want to consider a more general case, namely whether classification is possible even if a texture is explored from different angles and distances. Furthermore, the robot generates sensory stimulation not only by moving the whole body, but also by moving the whiskers actively. We have approached this question twofold: first, we recorded different textures from different angles and distances and trained a neural network to classify these textures. In a second series of experiments, we let a robot explore an environment equipped with different textures and trained a network with these self-acquired data. During a separate testing phase, the classification of the sensory input was recorded and evaluated.



(a) (b) (c)

Figure 9-1: **a)** Photograph of the data collection setup with rough carton. The 6 whiskers of the artificial whisker array can be moved synchronously by one servo motor. The whiskerarray was placed at different distances and angles towards the texture. **b)** Schematic of the layout of the seven positions at which data was recorded with respect to the texture (indicated as a striped bar) **c)** Example of one sweep of raw data and the recorded motor signal. The borders between sweeps as extracted by the algorithm are marked with arrows.

9.2 Materials and Methods

The goal of this series of experiments was to assess the robustness and the discriminatory power of the whisker sensors under real-world circumstances. Detailed data analysis has been performed elsewhere [47]. We used a microphone-based whisker sensor with natural rat whiskers as described in [98]. A single whisker hair of approximately 5 cm is glued to a capacitor microphone. Mechanical stimulation is thus transduced to a deformation of the microphone membrane. The resulting signal is amplified and recorded by the computer. Six such whiskers are assembled in an array of two rows with three whiskers. They can be moved actively by one servo motor to perform a periodic synchronous sweep at a frequency of 1 Hz. The construction of the whisker array has been described in detail in [46].

9.2.1 Data Acquisition

We collected a dataset containing four different textures: 1) smooth metal, 2) sandpaper 400, 3) sandpaper 80 and 4) rough carton recorded at seven different positions (see figure 9-1(b)). At position 1, the base of the whisker sensor is at a distance of 2 cm from the texture. The positions in one column are each 1 cm apart. The whiskers were actively moved across the surface of the texture and the position of the servo motor was recorded simultaneously. Data acquisition was performed using a

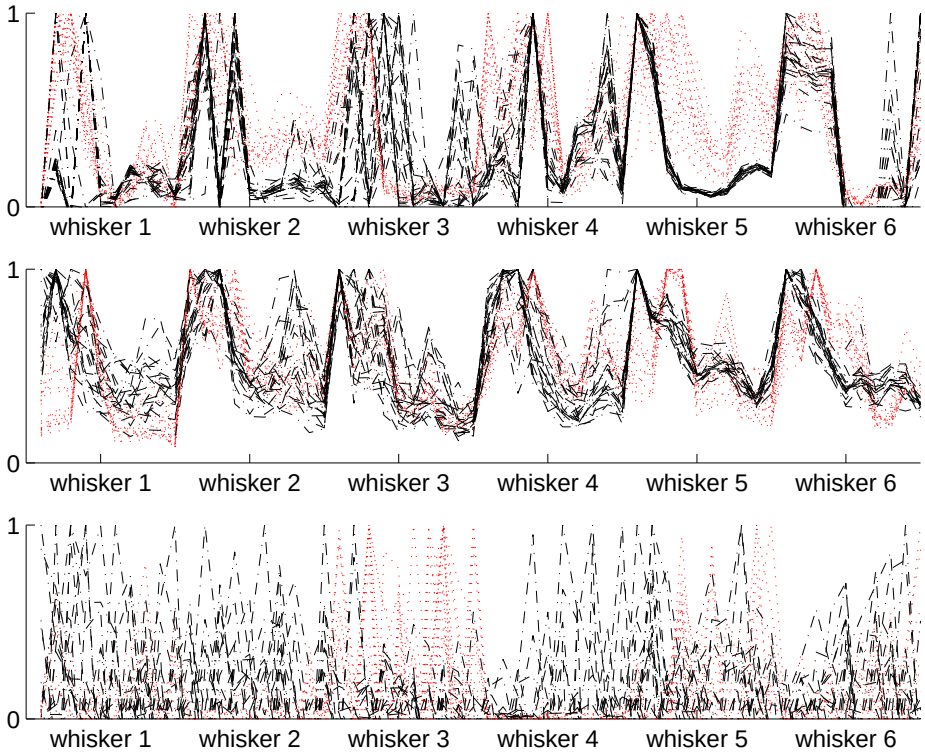


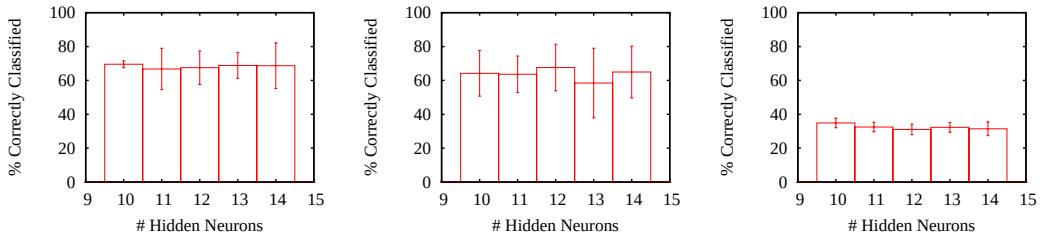
Figure 9-2: Cumulated feature vectors of twenty sweeps in one position of texture 1 and texture 4. The dotted line indicates texture 1, dashed line texture 4. The preprocessing used was **Top row:** Smoothed raw data, **middle row:** fft and **bottom row:** PCA components after a spectrotemporal analysis.

National Instruments Data Acquisition Card (DaqCard 6036E) at 4 kHz per channel.

For the robot experiments we used an open environment. Half of the surface was lined with a rough carton surface, the other half was left blank, displaying a smooth metallic surface.

9.2.2 Feature Extraction and Discrimination Capabilities of Recorded Data

Previously, we have shown that it is possible to generate texture specific signatures from power spectra of whisker signals (see [47]). Such a signature relied on several sweeps and covered frequencies up to 1 kHz. For a system behaving in real time, we sought to reduce the dimensionality of the input vector further. Three different preprocessing methods for feature extraction were tested: Spectrotemporal analysis, fourier transform convolved with a Blackman window of 70 data points (57 Hz) and raw data also convolved with a window of 57 Hz. In all three cases, the dimensionality



(a) (b) (c)

Figure 9-3: Mean percentage of correctly classified samples using **a)** smoothed raw data and the ten highest values of each whiskers in blocks of 75 ms. **b)** FFT preprocessing **c)** spectrogram preprocessing with subsequent PCA.

was reduced to 10 values per whisker yielding a feature vector with 60 values. The raw data and the fourier transformed data were divided in 10 windows (the first 750 ms of each sweep and the frequencies between 1 and 1000 Hz) of 75 ms and 100 Hz respectively. Then the highest value of this window was passed as input to the network. Examples of 20 such input vectors of two different textures are shown in figure 9-2.

9.2.3 Training the Neural Network

To identify and evaluate different features, a standard backpropagation network was used to classify previously recorded textures. Please note that the purpose of this experiment was not to postulate a specific biologically inspired architecture, but to evaluate the potential of the features used and the setup as a whole under real-world conditions. Any other statistical classification algorithm could have been used as well. Training was done using the Levenberg-Marquardt algorithm as implemented by the Matlab Neural Network Toolbox [1]. For all neural networks described in this paper, we trained ten runs with different random initializations and between 10 and 14 hidden layer neurons.

Since the whiskers were stimulated by actively sweeping over the surface, the proprioceptive signal from the motor identified the repeating elements. Multiple sweeps of the same texture were thus extracted from one continuous stream of input. One such sweep together with the motor signal is shown in figure 9-1(c). Together with the remaining five whiskers, this constitutes one sample of input for feature extraction and subsequent neural network training.

For each texture, one minute of data was recorded at seven different positions systematically varying the distance and angle of the whisker array with respect to the presented texture (figure 9-1(b)). A second set of data was recorded separately to be used for testing the network.

9.2.4 Evaluation of Network Performance

To test the classification and generalization, each trained network was simulated with the test data and a hit matrix (as in figure 9-4(a)) was computed by determining the output neuron responding most strongly and comparing it to the desired output neuron. From the hit matrix, the percentage of correctly classified samples was computed. After feature extraction using fourier transformation with subsequent dimensionality reduction as well as the temporal analysis of the raw data, the neural network was able to classify not only the training set but also the test set (figure 9-3(a) and 9-3(b)). The best classification for raw data was 75 %, for spectral analysis (fft) it was 74 %. Usually, about one of the random initializations resulted in a network unable to classify the testdata above chance. This is the reason for the rather large errorbars in figure 9-3(b).

Figure 9-3(a), 9-3(b) and 9-3(c) show the mean number of correct responses for the three different types of feature extraction for 10 different random seeds and different numbers of hidden neurons. Spectrotemporal analysis followed by principal component analysis was not able to learn to discriminate the four textures, mean correct responses range between 25 % and 39 %.

Figures 9-4(a) and 9-4(b) show the hit matrices for the testdata with a sample neural network. Bright color indicates many entries. The bright diagonal shows that the network classified the textures correctly in most cases. More interesting is the interpretation of misclassifications: most mistakes occured for the two sandpapers (textures 2 and 3). Smooth metal and rough carton were rarely confused. The distinction between these two textures was especially clear between feature extraction using spectral analysis, therefore it was used in the robot experiments.

9.3 Classification of Data Recorded on a Mobile Robot

First tests with the robot were conducted using the same features and neural network structure as determined to be appropriate with recorded data. However, when the

robot did not use any sensory feedback to adjust its position with respect to the encountered surface, often it did not get stimulation in more than two whiskers. Data recorded under such conditions did not result in successful classification (data not shown). Therefore, the whisker data was used to roughly position the robot such that at least four whiskers were stimulated.

For this behavior, the robot was equipped with a few motor primitives: It explored the environment while whisking actively for obstacles and explorable textures. Upon contact, the robot stopped and acquired a few whisks of data. Depending on this sensory input, it either logged data or repositioned slightly with a fixed turning behavior in order to achieve stimulation in at least four whiskers before acquiring data. The training signal necessary for the backpropagation algorithm was delivered manually. In unfortunate spots such as ambiguous corners, the robot was repositioned manually.

After a total of 150 encounters which were shared about equally between the two whisker arrays, the first 3/4 of the encounters of each side of the robot were used to train the neural network, the last fourth of encounters was used to test the performance. Please note that between every encounter, the robot moved for a minimum of 2.5 s including turning on the spot. This ensured that each instance of acquiring data was actually done at a new orientation and at a different spot. On average, the left whisker array classified correctly more often than the right whisker array. The mean values on the left side ranged between 65 to 76 % correctly classified samples with the best network classifying 85 % of the test samples correctly (figure 9-4(c)). The right whisker array on average classified between 63 % and 67 % percent of the samples correctly. The maximum of correctly classified samples was 76 % (figure 9-4(d)). The differences found between the two whisker arrays can depend on several factors which cannot be decided on the basis of the current experiments. Possibly, the quality of the whisker sensors varies. Another source of variation is that the robot acquires data on its own and thus it may be that one side accidentally records data more apt for classification.

9.3.1 Behavioral Experiments with the Robot

The same neural network structure was used for the robot as was tested previously in the simulation described above. For each of the two whisker arrays with six whiskers a neural structure was created: this right and left hemisphere were fed with the signals from the respective whisker arrays and trained individually. During a behavioral testing phase, the previously trained robot explored the environment. Upon contact

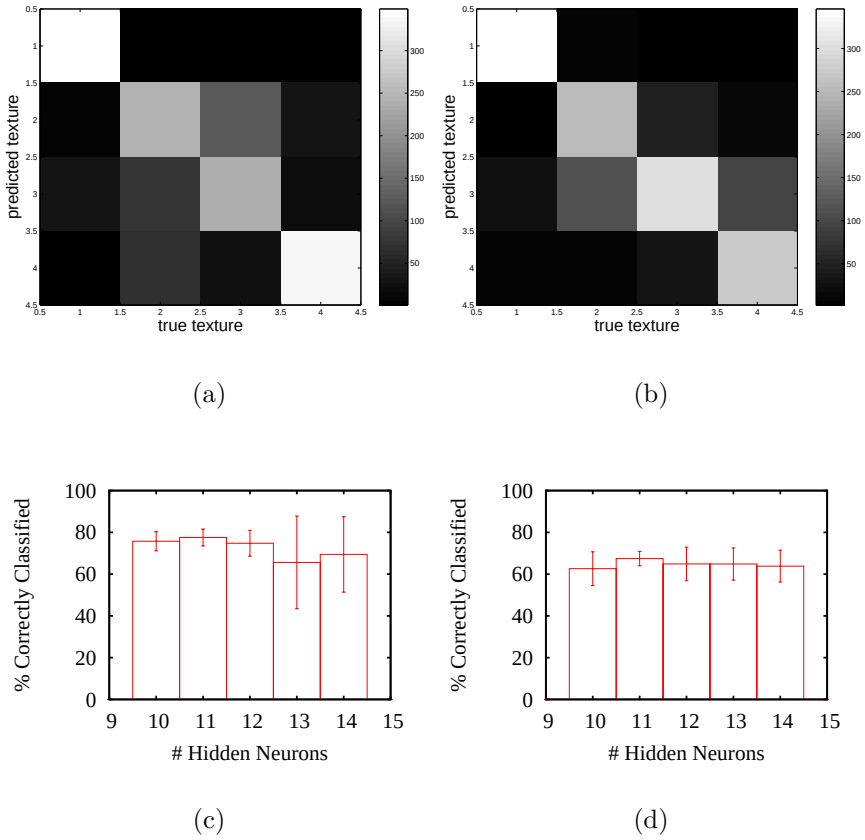


Figure 9-4: **Left** Sample hit matrix on all recorded positions and textures with **a)** FFT preprocessing and **b)** smoothed raw data. The textures are from 1 to 4: smooth metal, sandpaper 400, sandpaper 80 and cardboard. **Right** Mean percentage of correctly classified test samples recorded with a mobile robot. **c)** Left whisker array and **d)** right whisker array. The textures to be discriminated were smooth metal vs. rough carton.

with a texture, it was palpated for 9 seconds of which five sweeps were used for classification. Depending on the resulting classification, the robot responded by turning by 30° or by 120° away from the texture. Given this behavior, we expect the robot to spend more time in that half of the arena, where the turning angle is smaller. The resulting trajectory should thus cover the respective part of the arena more closely. To evaluate the robot performance, each run was recorded with an overhead camera and the robot was automatically tracked using the KLT library [140]. As a control condition, the robot behaved as described above, but instead of using sensory input for classification, the type of texture was supplied by the experimentor. Here, only slippage of the wheels or physical hindrance e.g. due to the cables can possibly induce

deviation from a perfect behavior.

In the actual experiment, the robot classified whisker input with the neural networks trained as described above. To ensure that a behavioral pattern was actually induced by correct classifications and was not an artefact of the allocation of texture type and turning angle, this allocation was also switched.

9.3.2 Results of the Behavioral Experiments

In the control condition shown in figure 9-5(a) it is apparent that the robot spends much more time close to the smooth metal. It also reliably turns away from the carton. This is due to the different preprogrammed turning angles. Reversing the angles also reverses the overall impression (figure 9-5(c)). During the actual experiment, the classification depended solely on the sensory input acquired by actively whisking any surface encountered during exploration. Figure 9-5(b) shows such a run: the robot spends more time close to the metal coated walls. This is due to the lower angle with which it turns from the texture classified as metal. Larger turning angles can be seen well for encounters with the rough carton coated walls.

The same holds true when the turning angles are reversed (figures 9-5(c) and 9-5(d)). Here, the robot turns with a 30 angle from rough carton and with a 120 angle when palpating smooth metal.

9.4 Discussion and Future Work

Tactile discrimination based on whiskers is still a young research area. The experiments described above try to fathom the potential of artificial whiskers for haptic sensing both statically and on a robot. For this purpose, a standard classifier was used, namely a backpropagation network.

Since whiskers are potentially very interesting tactile sensors for robots, the main focus of the experiments was to assess how reliable whisker-based classification is without strict control of position and orientation. The results of neural network simulation of data recorded at different but defined positions are promising. Even with only few inputs and a standard preprocessing such as fourier transformation, classification of four different textures with about 70 % correctly recognized textures based on only one sweep has been achieved.

To test whether this would hold true for the continuous space of possible distances and orientations on a mobile robot, robotic experiments were conducted. In this series

of experiments it became apparent that it is more difficult to achieve classification behavior under real world conditions. Firstly, sensory feedback based on whisker input had to be introduced to avoid active exploration in situations when only one or two whiskers touched the surface. Having limited the range of possible positions to those, where at least four of six whiskers were activated, test data could be classified to some extend, but not without mistakes.

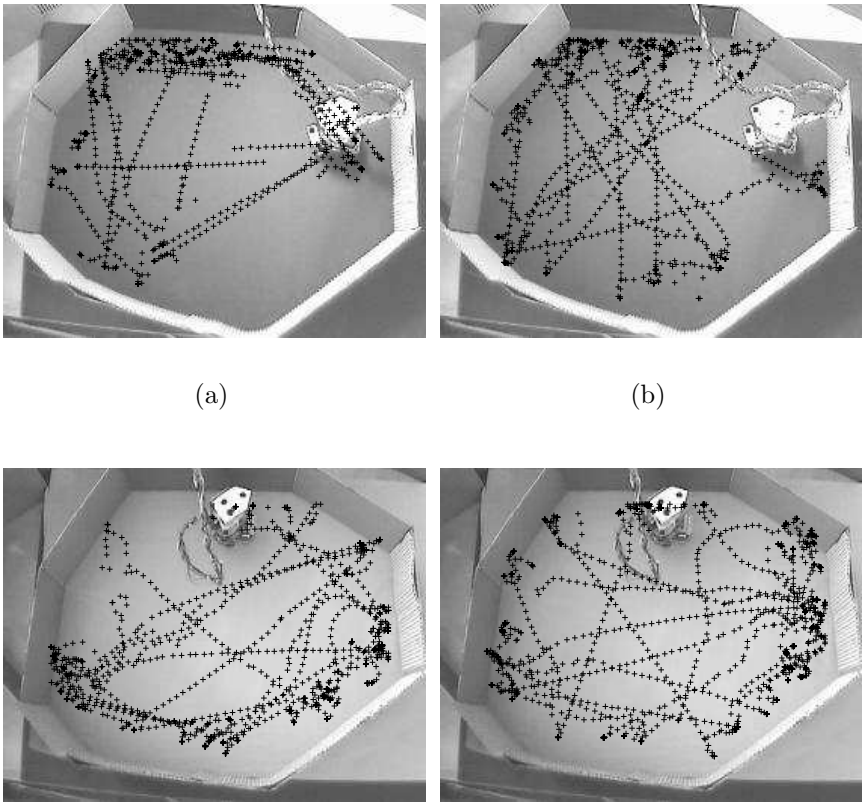
Based on these results, a lot of experiments can be proposed. For example, we want to test the whisker-based texture discrimination of the robot in a behavioral task comparable to experiments on rats. We have already built a maze with variable number of arms. The robot should be able to chose specific arms based on textural information at the walls of each arm. For this task it will probably be necessary to improve the reliability and the discriminatory capability of the system. While we cannot exclude that the preprocessing chosen for these experiments is not optimal, we believe that to achieve more reliable classification sensory-motor coordination might be used on two levels. Firstly, feedback from the whiskers could be used adaptively to orient the body of the robot appropriately with respect to the texture. Rats for example are reported to prefer a distance of 2 cm from their whiskers to an object or texture [38]. Secondly, the whisking behavior itself could be influenced by sensory feedback. Varying the speed or amplitude of whisking could possibly help to resolve ambiguities. Again, there is evidence from behavioral rat studies that the whisking frequency is not always the same but might be varied from one whisking cycle to the next [27]. Most probably, both proper orientation and adapted active exploration are crucial for fine texture discrimination and thus complement the stereotyped active exploration that was investigated in this paper.

In addition to behavior exclusively based on whiskers, the robot is already equipped with an omnidirectional camera. This opens up the possibility of investigating behavior based on two different sensory modalities.

9.5 Conclusion

In this paper, we have shown that it is possible to classify tactile data of different textures acquired with artificial whiskers. In a first series of experiments, we have shown that four textures consisting of a smooth metallic surface, two different sandpapers and rough carton can be classified even when the position of the whiskers with respect to the texture is varied considerably. This result is a prerequisite for using the sensor on a robot without highly precise position control. In a second series of

experiments, a mobile robot was used to acquire data in an open environment with walls of different tactile quality. Here, the positions of the robot with respect to the wall were not specified but only limited loosely. Our experiments have shown that classification is not entirely reliable under real-world conditions. However, given sufficient data, a rough discrimination has been achieved. In the future we will use more biologically inspired sensory processing and sensory-motor feedback to refine the tactile capabilities.



(a) (b)

(c) (d)

Figure 9-5: Trajectories of a single run. Each cross indicates the robot position during one frame of a consecutive image sequence. The background shows the actual robot arena with the robot as seen from an overhead camera. The bottom and the right wall are coated with rough carton, the upper and left walls are made of smooth metal. **Top row:** The robot turns from rough carton at a larger angle than from the texture classified as smooth metal. **a)** Classification supplied by the experimentor and **b)** classification according to sensory input. **Bottom row** The robot turns stronger from smooth metal (120° angle) than from rough carton. **c)** classification supplied by the experimentor and **d)** classification according to sensory input.

Chapter 10

Discussion and Conclusions

In the preceding chapters, we have presented an embodied approach to study several aspects of tactile sensing based on artificial whiskers. In what follows, we will summarize the main results and discuss their implications for robotic research as well as biology. Details on the experimental setups and results can be found in the respective chapters. Here, we will focus on the insights gained not only from individual experiments but also by synthesizing a coherent view. Two main strands of research were followed, namely the relation between morphology, task and control, and second, the investigation of tactile perception using whiskers. In this context, we have studied the interplay of sensory morphology and active sensing including both active motion of the sensors as well as movement of the whole robot body (figure 10-1).

This discussion is structured as follows: we will recall the main results and points of discussion from the individual publications presented in chapters 4 to 9. Additionally we will include more general aspects and implications and draw final conclusions. In section 10.4, we will discuss future directions of biorobotic research using whiskers.

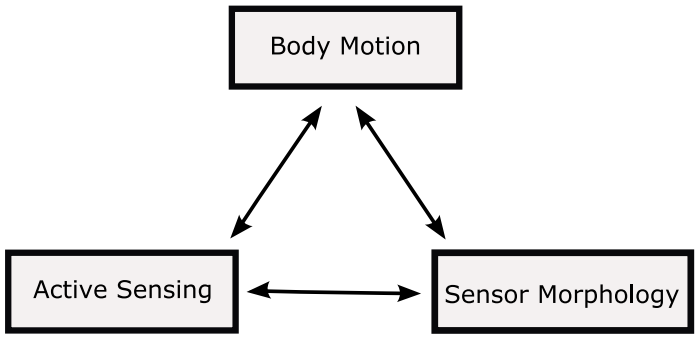


Figure 10-1: Main influences on robot behaviors discussed.

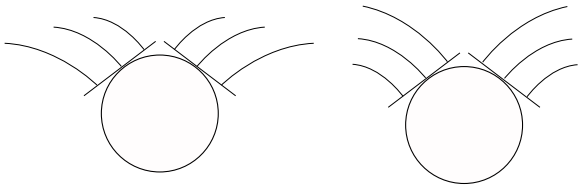


Figure 10-2: Primary morphologies discussed. On the left, the morphology commonly found in nature, on the right, we see the morphology best suited for obstacle avoidance.

10.1 Sensory Morphology and Control

Whiskers are found in a wide range of animals. Among them are large animals such as walruses and small ones like mice. Habitat, preferred food and typical behavioral patterns differ largely. Most sensory organs like eyes or ear laps show strong morphological adaptations to the ecological niche of the animal. Along the same lines, Brecht et al. [21] have studied several animal species and measured the lengths of the whiskers within the whisker pad. Across species, they find the same morphological pattern, i.e. long whiskers towards the back and side, and short whiskers in the front of the animals (see figure 10-2, left).

While it is nearly impossible to change the natural arrangement and whisker lengths in animals to investigate their influence on behavior, this can be done easily on a robot. A series of experiments presented in this thesis have investigated the influence of whisker length and location on the behavior of the robot. In what follows, we will recapitulate the main findings and discuss their implications.

10.1.1 Reflex Control and Morphology

The first experiment described in chapter 4 focused on morphology and therefore employed purely reflex-based control. The arrangement of whiskers was varied in two dimensions: first, the angle of each whisker array with respect to the robot body, second, the length of the whiskers within the whisker array, i.e. between long whiskers in the center versus long whiskers laterally.

Six morphologies were tested on a single task, namely obstacle avoidance. This is arguably one of the most basic sensory tasks associated with locomotion. But for a mobile agent it is crucial that it not only avoids objects at all costs but that it is still able to access its whole environment and approach objects closely. In other words, a strategy to avoid obstacles by not moving at all or by keeping a maximum

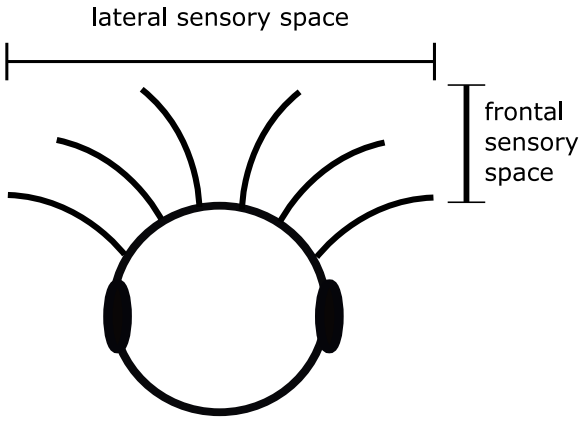


Figure 10-3: Schematic of the robot and its whisker sensors with indication of the frontal and lateral sensory space.

distance is not appropriate as it will limit the agent's range. Premature avoidance results in large distances between agent and obstacles or walls, it may even keep the agent out of narrow spots. Therefore, we evaluated the robot behavior both on how well it avoided obstacles as well as on its coverage of the experimental arena.

We found that the morphology with long whiskers in the front and short whiskers on the sides performed significantly better than the others. The angle between the two whisker arrays in this morphology was almost perpendicular such that the arrays were about tangential to the robot body (see figure 10-2, right). Specifically, this morphology was best able to pass through tight spots

To interpret this finding, we have to consider the relation between the solid physical dimensions of the robot body including the rigid supportive parts of the whisker array and the compliant whisker sensors. We call these the physical vs. the sensory space (see figures 6-1(a) and 10-3). The sensory space is determined both by the length of the whiskers within the whisker array as well as by the position of the two arrays on the robot body. The performance of different morphologies varying these two parameters shows a sharp peak [48]. For an even coverage of the arena, the sensory and the physical space of the robot have to match. The sensory space extends both frontally and laterally beyond the physical space of the robot (see figure 10-3). If the lateral sensory space largely exceeds the physical dimensions of the robot, and the robot is strictly reflex-driven, it cannot approach objects or walls close enough to fit through tight openings. Frontally, in the principal direction of motion, the whiskers have to be long enough to detect obstacles early, meaning that the sensory space has to be large enough to allow for effective avoidance.

10.1.2 Learning and Morphology

Pure reflex control is not the sole behavior of advanced animals such as cats or rats. They have well developed brains with a great capacity for learning and adaptation. To test whether learning would broaden the peak in the performance, in other words, whether the strong preference for a particular arrangement found for reflex-driven behavior without adaption could be softened with a learning scheme, we tested three morphologies on the same task. Based on the experiments described above, two were chosen to represent strong differences in the lateral width of the sensory space. A third morphology was included with a maximal sensory space frontally as well as laterally. This time, the robot learned to adjust its reflexes to the amount of stimulation it received through the whisker sensors. For practical reasons, the learning time was restricted. The performance was again measured by how well the area was covered and how long the robot moved.

We found that the morphology with long whiskers in all positions performed best. It should be noted that a) again one morphology outperformed the others, and b) with learning the robot was able to take advantage of long side whiskers. In other words, a wide sensory space was not a disadvantage anymore. In an abstract sense, the robot had acquired reflexes appropriate for its physical dimensions.

10.1.3 Evolving Morphologies

In the robot experiments described so far, only a discrete subset of the continuous space of possible whisker morphologies was tested. To potentially sample all morphologies as well as vary both the morphology and the control at the same time, we developed a simulation of a robot[1] with artificial whiskers designed to closely match the robot experiments. In simulation, we then employed artificial evolution working both on the control (the turning speed and angle) as well as on the morphology, namely the length and distribution of the whiskers on the robot body [17]. The robot was simulated as a circular, two-wheeled robot similar to the Khepera platform. The whisker signals were thresholded to signal collisions. A fitness function was chosen which ensured that the robot moved constantly: the robot had to navigate towards randomly placed targets without hitting obstacles. The fitness of an agent was computed as the number of targets found minus the number of collisions.

Evolved whisker morphologies were in good agreement with the findings of the robot experiments, namely long whiskers in the front of the robot and shorter whiskers

[1]The ODE simulations described as part of chapter 6 were programmed by Simon Bovet.

towards the sides. This arrangement allows an early detection of obstacles in the front of the robot while restricting the sensory space laterally to the physical dimensions of the robot. In particular, the lateral space of the robot was matched closely while there was more variation on the frontal sensing range.

In a second series of experiments, the influence of the compliance of the whiskers was tested by comparing rigid whiskers modeled as a beam with only a base joint against flexible whiskers consisting of several elements connected by joints. We found that the fitness of agents with flexible whiskers evolves faster than in agents with rigid whiskers. Furthermore, the fittest agents with flexible whiskers showed a larger variety of morphologies while the evolved morphologies of rigid whiskers were much more uniform.

10.1.4 Testing Morphologies on a Wall Following Task

As already indicated previously, it is not always a favorable strategy to stay away from objects. As explained in section 2.1, whiskers are advanced tactile organs. It is highly probable that the natural morphologies are well adapted and optimized to the most important functions whiskers have for the animal. Many animals with especially well developed whiskers navigate under conditions unfavorable for vision. From our own intuition, we know that in darkness it feels safer to feel one's way along a wall than to walk into the open without visual or tactile feedback. Therefore we chose wall following as a second highly relevant task which an agent should be able to perform with whiskers.

We tested the same three morphologies as in the learning experiment and evaluated the smoothness of the resulting trajectory as well as how strong the number of activated whiskers varied. Both measures indicate how stable the wall following is both on the level of sensory activation and on the behavioral output.

We found that the whisker morphology most similar to the natural arrangement performs best on the wall following. This suggests that whiskers are more optimized towards wall following than towards pure obstacle avoidance.

10.2 Texture Discrimination Capabilities

It is known that rats have superb tactile faculties. To explore the tactile capabilities of the artificial whiskers, we conducted several different studies. While there is a large body of theory and experimental know-how about the visual modality both in biology

and in artificial intelligence, little was known about whisker-based tactile processing when this thesis was started. We have focused on texture discrimination as a tactile behavior and studied a number of aspects. We proceeded from a tightly controlled experimental setup with only one whisker (chapter 7) to texture discrimination with an active whisker array (chapter 8), and finally to real world conditions where we achieved texture discrimination on a mobile robot (chapter 9).

10.2.1 Learning of Spatiotemporal Receptive Fields

In a first series of experiments described in chapter 7, we recorded a large set of whisker data by manually sweeping a single whisker across natural textures as well as actively whisking textures with a single whisker. In the first case, the whisker was swept over the texture in a single, long sweep while in the latter case, the whisker moved back and forth rhythmically. We trained a set of neurons to respond sparsely to the spectrograms computed from pieces of the recorded data. Sparse coding means that any single neuron should respond only to a small subset of the training data. Furthermore, the whole population of neurons was trained to respond to different spectrotemporal patterns, i.e. they were optimized to be active sparsely across the population. Receptive fields with a large variety of spectrotemporal characteristics emerged. Most neurons were localized in space and time, i.e. they responded to signal in a specific frequency band at a particular moment within the presented sweep. Potentially, these neurons can be used to discriminate different textures by the specific activity patterns of the neurons.

This work was continued and extended by Hipp et al. [68] He showed that with a similar optimization function, he could train receptive fields useful for texture discrimination.

10.2.2 An Active Whisker Array

To extend our single whisker studies to multiple whiskers, we recorded a set of different textures with an actively moving whisker array. This array was composed of eight whiskers in two rows. A single servo motor synchronously tilted all whiskers at their base generating a sweeping motion [47]. From the training set we generated typical spectral signatures for all textures. These signatures were used to classify separately recorded test data. For the classification, we computed the Euclidian distance between the test power spectrum and all signatures. The smallest distance identified the type of texture. With this simple classification, we were able to correctly discriminate up

to eight different textures considering all whiskers and multiple sweeps.

In chapter 8, we not only showed that the whiskers are capable of discriminating different textures, but we were also interested in whether it was actually necessary to have several whiskers. Figure 8-7(a) shows that considering more whiskers for classification improved the performance. Assembling several whiskers in an array adds redundancy to the system. Usually, we consider sensory systems to be redundant if sensing relies on different physical mechanisms such as electromagnetic waves stimulating a vision system complemented by mechanical haptic sensations [123]. A trivial type of redundancy is duplication of sensors such as adding a second camera recording the same image. Here, we encounter an intermediate level of redundancy since the whiskers are not identical. As shown in chapter 3, whiskers with different lengths have different material properties and thus are capable of showing different sensitivities to complex input. Furthermore, neighboring whiskers within one whisker array touch partially overlapping parts of the texture, therefore they acquire partly redundant information. This illustrates the advantage of embodiment and in particular of building a physical robot. In a simulation, variation in the sensor properties have to be included explicitly and are subject to designer-based decisions. In the physical robot, such variation e.g. in the material properties of the whisker sensor, arises naturally and allows for rich interactions between the robot and its environment.

A second question we investigated in this paper concerned the importance of motor feedback. Whisker data was recorded by actively sweeping the whiskers across different surface structures. While sweeping, we recorded the motor commands to be able to correlate sensory data to motor action. By comparing the classification performance of randomly selected data pieces with sweeps segmented according to the motor signal, we found that incorporating motor feedback allows to discriminate more textures than when the signal was cut at random locations. We conclude that active motion is useful as it structures the sensory data and thus allows to extract meaningful pieces such as a complete sweep of whiskers across the texture.

These experiments confirmed that the sensor is capable of discriminating different textures. The artificial whisker setup allowed to decouple the sensorimotor loops which are always present in the healthy animal. The dynamic interaction of multiple whiskers with natural textures in the real world as well as the integration of motor feedback for sensory segmentation proved to be central elements for improving the discriminatory power.

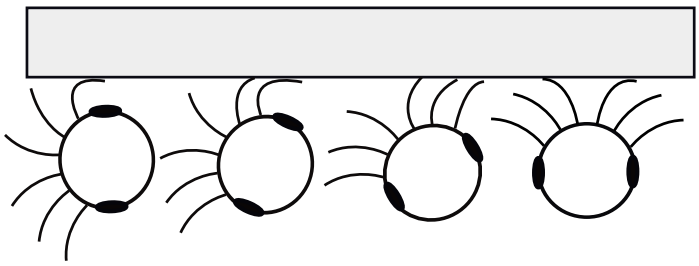


Figure 10-4: The robot can hit a wall in a wide range of possible orientations. Furthermore, a variation in distance can occur at all positions (not shown).

10.2.3 Moving Towards the Real World

On a mobile robot, distance and orientation of the agent towards objects are subject to variation. Since ultimately, the whiskers should be used on a mobile agent, it had to be determined whether the whiskers can also be used over a range of angles and distances. A set of data was recorded by actively sweeping the whiskers over four different types of textures. Both the distance and orientation of the whisker array towards the textures were varied systematically to simulate the situation on a mobile robot. For classification, a multi-layer perceptron was trained on all textures and positions and tested on a separately recorded test set. These four textures were successfully classified. Only few misclassifications occured, most of them confusing two sandpapers of similar roughness. The focus of this experiment was to show that textures can be discriminated even without tightly controlled positioning.

10.2.4 Robot Experiments

As a next step, the robot was placed into an arena with walls either covered with rough carton or displaying a smooth metallic surface. The robot drove straight until sensing the wall. When a wall was detected, the robot stopped and actively acquired whisker data. Both whisker arrays acquired data which was stored separately for later training of two separate networks.

In a first series of experiments, no correction of the robot's position towards the wall was performed. The resulting range of orientations (for illustration see figure 10-4) was therefore very large even containing positions with only few whiskers briefly touching the wall during the whisking cycle. Without sensory feedback on the robot position, no classification above chance level was achieved.

In a second series, basic sensory feedback was included to position the robot.

Already with a reflex-like sensorimotor loop, the robot was able to correctly classify the textures significantly above chance level. Thus, integrating body motion and sensing clearly improved the quality of the sensory input and in consequence the behavioral performance (see figures 9-5(b) and 9-5(d)).

10.3 General Implications

In what follows, we will discuss our results in the context of the current literature and recent biological findings. We will present more speculative hypotheses about the function of specific whisker morphologies. Finally, we will broaden the discussion and discuss related work as well as possible future directions, including refined sensory-motor coordination, more realistic biological models which focus on the neural dynamics and the coupling of sensory and motor system. They include synchronization mechanisms and recurrent interactions which generate expectations and predictions.

10.3.1 Implications for Natural Whisker Morphologies

In the previous discussion, we have already mentioned the relation of the morphologies tested in our experiments to the most common natural whisker arrangement on animals. Here, we discuss the implications and resulting hypotheses.

One of the reasons for engineers to study natural systems is that by evolution, these systems have been optimized for specific tasks and environments. However, the selective pressure works on the whole agent and trade-offs occur at all levels. In the whisker system, competition for resources such as energy and processing power (e.g. brain areas) occurs between the different sensory modalities, different whiskers and between optimization between different tasks. Here, we have not studied the visual modality, but it should be kept in mind that most animals have vision and use it extensively for obstacle avoidance (see discussion in chapter 6). Therefore, it fits the picture well that the morphology most successful at following a wall and not the one most successful at avoiding obstacles, most closely resembles the natural whisker morphology.

Biologists who study the behavior of an animal always face the problem that animals are able to solve tasks using a variety of behavioral strategies and performing other functions simultaneously. For example, navigating through a maze - even in darkness - can be achieved by following the walls closely or by walking straight until a wall is touched. It is therefore not possible to unambiguously estimate the contribu-

tions of various task strategies to the development of a specific sensory morphology. Using the synthetic methodology and building a robot allows to study the relation between morphologies and specific tasks, and we were able to show that in natural systems, the morphology of the whisker pad is adapted more towards following a wall than towards avoiding obstacles.

It should be noted that the described experiments were conducted with passive whiskers so the results should primarily be compared to animals which do not whisk, i.e. they do not sweep their whiskers actively in order to palpate an object. A prominent example are cats. While cats have excellent vision, they are reported to use whisker for example to estimate the width of openings and judge whether they will fit through - anecdotal evidence reports that cats with clipped whiskers have been seen to get stuck in tight openings.

But why do animals not have very long and equally long whiskers? Growing hair requires energy, so it is not advisable to grow it longer than necessary. Furthermore, each whisker in a rat can be actively moved by a sling muscle. The longer the hair, the heavier it is. Therefore, more energy is required to support and move the whisker. It has been shown that if cats are blinded at birth, they develop longer and stronger whiskers [127]. Since without vision, whiskers become more important, this suggests that cost and benefit for whisker length are well balanced.

Apart from these energetic considerations, we have shown in chapter 3 that whiskers of different length have different resonance frequencies. Some biologists hypothesize that these different resonances might be useful to decode the frequency components in a texture discrimination task. Likewise, Brecht et al. [21] have considered texture discrimination and morphology. They proposed that the morphology featuring long whiskers to the back and side, and short whiskers to the front of the animal should be particularly useful for exploring objects and surfaces because the whisker tips fall in a plane and therefore afford a large tactile pad (left, figure 10-2).

The specific contribution of the task of texture discrimination to whisker morphology remains an open question - especially since to our knowledge it has only been shown for rats [26, 56] and seals [35] that they are capable of discriminating complex object features such as textures or object size using their whiskers.

10.3.2 Implications for Tactile Perception Using Whisker Sensors

We have shown that it is possible to discriminate a broad range of textures with a fairly simple artificial whisker such as the one presented in this thesis. A single whisker is in principle sufficient for texture discrimination, but using several whiskers, we were able to more than double the number of discriminable textures.

Given that the sensor was new at the beginning of the work reported here, we had to first identify relevant features of the sensory signal. Using spectral analysis, we have been able to extract the appropriate information to discriminate textures. Many different variations of straight-forward spectral analysis have subsequently been used by different research groups [7, 10, 67, 108] and it has been shown that the product of frequency*amplitude is a very likely coding scheme of cortical somatosensory neurons [8, 10].

The fact that rats actively whisk objects or surfaces already suggests that active sensing plays an important part in achieving high resolution tactile perception. In chapter 8 we have shown that using motor feedback to structure the continuous stream of data massively improves the tactile capabilities. First directions in investigating the role of active sensing in rats are open-loop experiments where the facial nerve is artificially stimulated to produce whisking even in anaesthetized rats [10, 11, 143]. This reproduces the dynamic interactions between whisker and texture and thus provides natural input for the neural system. However, our experiments suggest that it will be crucial to use the feedback of the active whisking, namely the motor signal, for segmentation of the data stream.

Finally, we have shown that it is possible to use the whiskers on a mobile agent, both for basic locomotion tasks and to discriminate textures. Again, closing the loop between whole body motion and sensing was a prerequisite for the generation of "good" data. Following this experiment, it would be interesting to apply Lungarella and Sporn's [100] information-theoretic approach to quantify the effect of motor action on the sensory data. In their experiment, Lungarella et al. analyzed visual data from an active vision system capable of foveating on a salient feature of an input video. By centering for example a red square in the visual field, the entropy of the center of the camera image decreased significantly. Using the motor action of foveating significantly changed the statistics of the input data. To apply the same quantitative measure on active whisker-based sensing, we first have to chose a relevant task environment. A possible issue might address the task of keeping a constant distance to a wall.

Since distance greatly influences the frequency composition of the sensory input, such coupling of sensory whisker data to the body motion of the complete robot would enhance the discriminatory capabilities. First steps towards a tracking behavior based on visual and tactile input is discussed in section 10.4. A second possible question to address with quantitative measures of information self-structuring concerns the active whisking. While we have demonstrated the importance of taking the motor signal into account for sensory segmentation, the next step would be to vary the whisking behavior, e.g. the amplitude or frequency of whisker motion, to generate "better" data.

Related Work on Robotic Tactile Sensing Based on Whiskers

In the context of artificial whiskers, several groups have studied texture and object exploration with artificial whiskers. In the context of the AMouse project, Kim and Moeller have mounted two whisker arrays on a Koala robot and performed experiments on shape discrimination using whiskers [83, 84]. They have shown that they can estimate contact point and bending of a whisker touching an object. Combining several whiskers and active sweeping, they can discriminate different shapes on a mobile robot (see section 2.2). They show how to analyze active whisking data by incorporating aspects about the biology of the sensors such that shapes can be discriminated.

Robotic experiments which focused primarily on a biologically inspired neural network have been presented for texture discrimination. A group in Gerald Edelman's laboratory reports to have discriminated two different textures on a mobile robotic device [138]. Behaviorally, the robot was programmed to follow a wall such that three horizontally aligned whiskers always touched the wall. At certain places, the wall was decorated with pegs. Three such pegs formed a texture: they were also stacked vertically, either with or without a horizontal shift. By following the wall, the robot passively brushed its whiskers across these peg textures. Different peg arrangements induced temporally distinct signals in the whisker sensors. A neural network was implemented with a set of cells which respond with a range of temporal delays to input from a whisker which they call lag cells. These delays create a rich response pattern useful to discriminate between the temporally different activation in the whiskers due to the pegs. Temporal response delays have been used widely in robotic experiments on visual processing and are known as elementary motion detectors (for example in [73]). The behavioral output of the robot is a conditioned avoidance response to one of the textures: instead of continuing along the wall, the

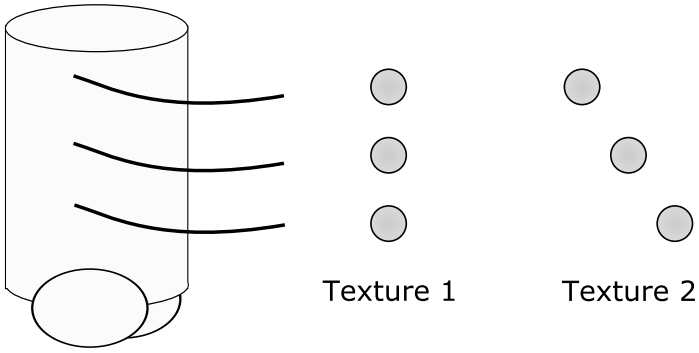


Figure 10-5: The robot depicted on the left side is equipped with whiskers which are perfectly aligned to the peg structures shown on the right. The two possible textures are represented schematically. Adapted from [138].

robot moves away from the wall.

In their experiments, Seth et al. [138] have carefully designed the neural architecture to show clearly different response dynamics to temporally different whisker stimulation. While this network incorporates biological considerations such as separate processing of single whiskers in barrels and integration on a later processing stage, only a single type of connection is plastic. The robot learns the connection between the output of the sensory processing and the neurons which elicit the avoidance reflex. Since this learning is tied to a simulated punishment, it is compared to operant conditioning.

In chapter 5, we have also employed a learning method which is related to a conditioning behavior, namely DAC. While both learning paradigms are related to operant and classical conditioning respectively, the purpose of employing learning is different. We have used learning to test whether adaptivity is able to compensate for differences in the morphology of whiskers. Seth et al. have employed learning to show that their processing of whisker signals can be used to discriminate between two tactile patterns by generating different behaviors.

Seth et al. describe a very interesting approach to the processing of whisker signals. However, a few questions remain. First, it is debateable whether they actually distinguish textures as the pegs constitute a distinct and very localized pattern. In our understanding, a texture contains small-scale repetitions, as for example the grains in a sandpaper. There, the grains are not arranged regularly eliciting precise temporal patterns, but instead vary around a mean distribution which generates our impression of roughness. It remains to be tested whether Seth's network can be generalized to integrate such irregular arrangements. Second, the central processing principle, the

lag cells responding with a range of temporal delays, have to be chosen manually. The neural network does not learn on any processing level concerned with sensory output. The third issue to this approach is that the whiskers only acquire data passively. Including active sensory exploration will certainly be an interesting addition to their experiments.

10.4 Directions for Future Research

Future research should pursue two directions, namely improve engineering related issues and explore conceptual questions related to multimodal exploitation and sensorimotor coupling, as well as coding and learning. From an engineering point of view, the sensor can be improved, and it could be extended to more functions and different habitats as for example water. A more conceptual continuation of this research should deal with the question how the sensor interacts with other sensory modalities such as vision, olfaction and audition. First experiments in this direction have already been performed by Simon Bovet [18, 19].

10.4.1 Engineering and Functional Extension

Whisker-based sensors have attracted increasing attention in the robotics community. In this thesis, whiskers were used to sense contact and surface roughness of objects. Other environmental features accessible to a whisker sensor are for example distance estimation, object shape or size, waves and turbulence in water or wind/airflow in air. As discussed in section 2.2, several groups have investigated contact point estimation to determine the distance between the whisker base and an object. These groups have based their analyses on single whiskers and on sensory information about the amount of deflection of the whisker.

Since the microphone-based sensor employed in this study does not measure the deflection of the whisker hair, distance has to be determined indirectly. A starting point is to derive distance indirectly by considering several whiskers within an array. If these whiskers have different lengths and the array is arranged in parallel to the object, the pattern of activation of the different sensors yields a rough estimate of the distance to the object. Alternatively, the microphone could be replaced by a sensing element which yields signals directly correlated to the angle of deflection of the whisker hair. Prototypes have been developed for example by Kim and Moeller [82].

A very interesting extension of the sensor would be to make it water-proof and adapt it to an aquatic medium. Lobsters for example use antennae for both tactile [163] as well as for olfactory tasks [87]. Dehnhardt's [36] discovery of the superb capabilities of seal whiskers for following turbulence trails leaves us wondering about the type of signals and how seals can cope with noise in the form of waves or other seals. Two issues involved are first, to make the sensor water-proof, and second, to find an appropriate whisker material. Water-proof pressure sensors are already on the market. Possibly, a whisker attached to such a pressure sensor could work similarly to the microphone-based sensor. Concerning the material properties of the sensory hair, it should be noted that water with its higher density exerts more force on the whisker. Therefore, a whisker for water applications should be stiffer than its counterpart in air. From a sample of seal whiskers, we have found that at least for the considered species, the whiskers are indeed very stiff.

10.4.2 Learning to Feel What You See and How You Move: Multimodal Architectures

First experiments have been performed using the same robot with its whiskers and camera by Bovet and Pfeifer [18, 19]. This work has concentrated on including basic features from different sensory and motor modalities rather than performing perceptually complex tasks based on a single sensory modality. To minimize designer-influenced biases, the processing architecture consists of homogenous neuronal groups for the visual, the tactile and the motor modality (see figure 10-6). Within each modality, neurons process different features such as change of sensory stimulation (known as optic flow in visual processing) or the previous state as well as a "desired" state which can be interpreted as a prediction of the next state of the system. All sensory and motor modalities are potentially coupled to each other. The strength of the neural connections depends on the correlations of activity in the respective sensors and motors, and is captured by Hebbian learning. Even though this architecture has not been designed for any particular task, it has been successful in a range of behaviors: the robot learned to follow an object such that the distance to the object was constant. During learning, it used both tactile and visual input. After learning, simulated activity in the tactile sense was sufficient to trigger the tracking behavior described above [18, 19].

In a second experiment, the robot learned to chose one of two arms in a T-maze according to a tactile cue at the entrance of one of the arms. Essentially the same

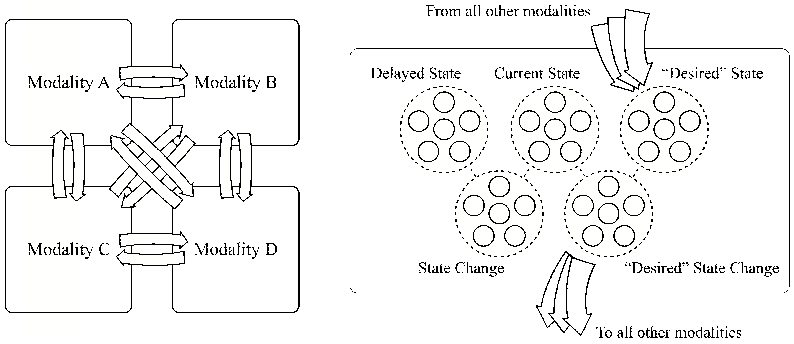


Figure 10-6: Multimodal learning architecture used with the AMouse robot. (a) Overview about the different areas. Note that they are fully connected. (b) Populations within a single area. Each population is specialized for some feature of the input. Figures courtesy Simon Bovet.

architecture was used which does not contain any explicit memory. Still, the robot was able to learn the task, even though reward stimulation and tactile cue were spatially and thus temporally separated [18, 19].

Using a different robot, Bovet and Pfeifer were able to show that different insect navigation strategies can emerge from essentially the same neural architecture. This suggests that the model incorporates sufficiently rich dynamics to allow for the emergence of different behaviors. It should be noted that the AMouse robot and its simulated neural system are well matched with respect to the complexity of the neural, sensory and motor systems, and it allows for interesting and varied behaviors.

Complex Perception: Binding and Neural Dynamics

At every moment in time, our perceptual apparatus generates coherent impressions of real world objects - seemingly effortless and instantaneous. Many years of research on computer vision have shown that what we take for granted - the separation of an object against its background for instance - is difficult to achieve in an artificial system. Therefore, artificial intelligence has turned towards neuroscience searching for the principles underlying perception in the real world. In neuroscience, one of the big questions in perception is the binding problem. In the brain, information is largely processed in parallel. But there has to be a mechanism which ties neurons responding to different features of the same percept together. Synchronization of groups of neurons which receive input belonging to the same percept is one of the most widely studied and influential mechanisms which can solve the binding problem

[22, 71, 138] (for review see [41]).

In the computational neuroscience and artificial intelligence community, several studies have therefore addressed synchrony in neural networks. While spike timing and the dynamics of spiking neural networks have been studied widely in the last years (for text books see for example [53, 130]), the major part of robotics research still uses non-spiking neurons. Spiking neurons are computationally more expensive, especially when learning is included. One of their advantages compared to conventional artificial neurons is that they reproduce properties of biological neurons more faithfully. In computational neuroscience, networks of spiking neurons are used to study network dynamics, especially with regard to synchronization phenomena in perceptual tasks. One very interesting example has been presented by Hopfield and Brody [70, 71]. To study the recognition of words under real world conditions, i.e. in the presence of noise, with different speakers/voices etc., they have implemented a network of weakly coupled oscillators consisting of pairs of spiking neurons. Each oscillator receives input from a specific frequency band, and the strength of its input decays linearly after presentation of this stimulus. The speed of decay of a range of these oscillators is chosen such that they will synchronize at some point in time because the frequencies of firing converge. Synchronized spiking in turn drives neurons in the detection layer (called γ neurons) above threshold (see figure 10-7).

These synchronizing oscillators have been shown to yield very stable recognition, even with high noise levels, varying talking speeds and different speakers. Furthermore, the same network architecture has successfully been applied to model odor recognition [22]. We have applied the model to data recorded with the artificial whiskers, but this approach was limited when applied to whisker data by the temporal structure which turned out to be inherently different from the speech data in the original example. For real-time robot control, the computational resources required for modeling of spiking neurons are still an issue. With increasing computer power, these difficulties diminish, and it is well possible that more robots will be controlled by networks of spiking neurons in the future.

Interesting work on visual binding on a real robot has been done by Seth et al. [138]. By modeling the key areas of the visual system with highly recurrent connections between different areas, they showed that synchrony crucially depended on these reentrant connections. Removing reentrant connections disturbs synchronization. Moreover, the behavioral performance of the robot decreased significantly. Seth et al. have modeled a huge network ($\approx$ 54000 neurons) with temporal parameters such as phase in each neuron to approximate properties of spiking neurons. To cope

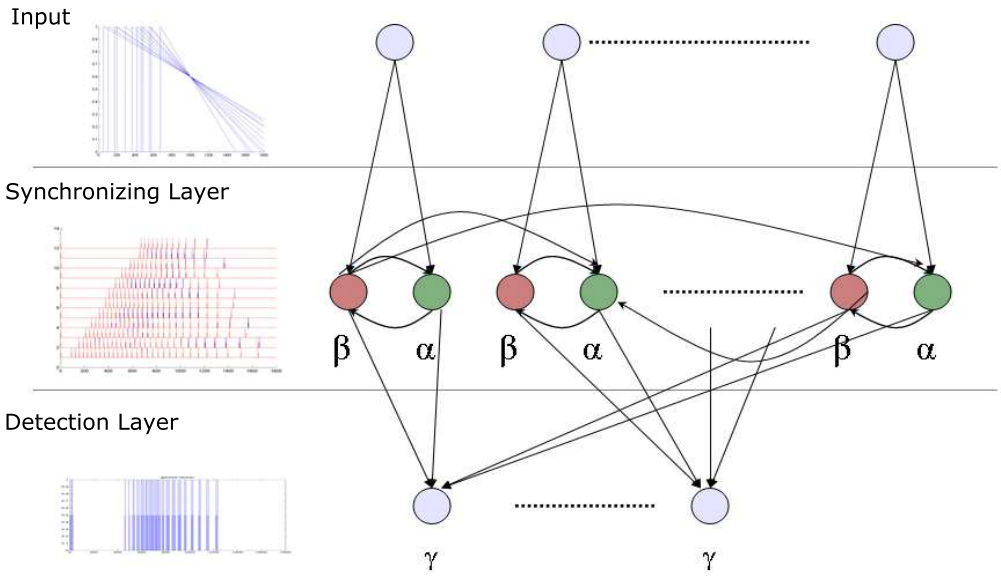


Figure 10-7: Simulated spike response of a synchronizing neural network for auditory word recognition. Left: Spike response of neurons in the respective layers. Right: schematic representation of the three network layers. Each oscillator is composed of an excitatory α and an inhibitory β neuron. For more details see text. This data has been generated during exploratory implementation of this network as it is described in [71].

with the challenge of real-time processing, a cluster of work stations was used to simulate the neural network and control the robot. Their experiments are therefore not only interesting for their findings on the importance of synchrony, but also show that it is possible to study complex and large-scale networks on a mobile robot.

Active Sensing and Top-Down Influences

In biological textbooks on sensory processing, the stream of information processing has often been depicted as a serial process from the peripheral sensors through different stations and higher cortical areas. This approach is often called bottom-up, but it should not be confused with the bottom-up approach of artificial intelligence applied in this thesis. Our approach is bottom-up in the sense that it employs the synthetic methodology of constructing an artificial model. Thereby we search for inspiration in biological systems and use these ideas to build robots. Bottom-up in this thesis is a methodological classification without a priori assumptions about the processing of signals, but instead indicates that a new system was built from scratch.

An important aspect studied in this thesis is the necessity for active sensory exploration. In our experiments, we were able to generate typical dynamic interactions between the whisker and its environment and study the discriminatory power with and without motor feedback which is difficult in a biological system. We have shown that the motor feedback is critical for achieving complex texture discrimination (see chapter 8). Integrating motor and sensory information to structure sensory input is one the most important design principles for embodied artificial systems (the principle of sensory-motor coordination [123, 125]). In chapter 9, we had to implement a reflex for positioning of the robot based on sensory input from the whiskers. Without this rudimentary sensorimotor coupling, classification was not possible.

Recently, interactions between sensory and motor areas have been shown in the rat barrel cortex: Ganguly and Kleinfeld showed that during active whisking, whisker motion and local field potentials in SI phase-lock [50]. Such phase-locking between the sensory reference signal and motor activity can serve to predict the position of the whisker during the whisking cycle, and it might be useful, e.g. for localizing objects [50, 143].

Top-down influences are widely studied in animals and humans (for review see [42]). In a complex world with a multitude of stimuli in many different sensory channels, complex motor systems and the need to be able to react fast and precise in order to survive, adaptive filtering of sensory input and preparation of motor responses are a necessity. Top-down connections and recurrent processing are a means

to apply previous experiences in the generation of expectancies and prediction. For robots acting in the real world as well as artificial intelligence systems designed to assist human beings e.g. at driving a car, such integration of previous knowledge into processing of sensory input will be crucial. Therefore, computational models are being developed to compute saliency including bottom-up and top-down processing.

An example from the field of vision is the group of Laurent Itti (see for example [112]). Itti and colleagues aim at modeling biological visual processing, and they have also started with first experiments for example on gaze direction [112]. These are interesting approaches which are also promising for future whisker research. However, much work has to be done both on the sensory side and on the neural modeling to achieve high-level attentional processes such as selecting salient stimuli from different sensory modalities. Intelligent and interesting behavior will be achieved by combining powerful sensing with design for emergence e.g. with the power to manipulate the environment, namely by moving, grasping and active sensing of the agent.

One of the most active research areas in artificial intelligence is the study of agents equipped with a variety of sensory modalities. In the previous section, we have described one architecture which contains different modalities. This approach is very promising, however, so far tactile sensing could only be efficiently included in a multisensory network as long as it was reduced to binary touch sensing. Possibly, new solutions have to be found to resolve the differences in the sensing time scales of different modalities, e.g. tactile sensing always requires a temporal delay unlike for example visual input where an image is available almost instantaneously. Better knowledge about tactile sensing by itself is a key prerequisite for complex multimodal architectures.

Another perspective on multi-featured processing has also been presented: the binding problem described above pertains not only to different features within one sensory modality, but includes the binding of features in different modalities which belong to the same object, e.g. we immediately recognize that the sight and smell of delicious food belong to the same object. Mechanisms such as synchronization have been studied which are able to resolve the binding problem. At the same time, we still lack detailed understanding of some single modalities. Much is known about the processing of sensory signals such as vision or audition, but in the tactile whisker system, many questions are still open or about to be understood. As discussed above, such knowledge can be necessary to apply specific models. In this thesis, we have targeted our research on understanding one sensory modality in different behavioral tasks and on a robotic agents. We are confident that these insights will prove useful

for research focusing on the exploitation of multimodal sensing.

10.5 Summary

The focus of this thesis has been to establish a new sensory modality, namely whiskers as a haptic sense. We have investigated basic relations between the task-environment and the morphology of the sensor. By building a robot model, whisker morphologies were evaluated on two basic locomotion tasks, namely obstacle avoidance and wall following. The morphology found in nature resembles most closely to the morphology performing best on the wall following task. This suggests that whiskers in nature are optimized more towards wall following than towards obstacle avoidance.

Whiskers are powerful tactile sensors capable of refined tactile perception. We have shown that challenging perceptual classification is possible even under real-world and noisy circumstances. Assembling several whiskers into an active array has two major benefits. First, using multiple whiskers adds redundancy as real whiskers have different material properties and respond with a rich pattern of frequencies to complex textures. Second, actively whisking a texture not only provides multiple inputs to the system, but including the feedback signal from the motor also structures the sensory input and thereby enables the agent to discriminate textures with a higher resolution.

To conclude, we have shown that to build a behaviorally successful agent with artificial whiskers, one has to consider the morphology of whiskers in relation to the task of the agent. Furthermore, redundancy of the sensors as well as active sensing are key elements to achieve complex perceptual capacities. Throughout this work, insights from biological systems have been incorporated into the design of experiments and of the robot. We have also been able to complement biological research: Physically building a robot has allowed us to identify the relationship between a specific task and the morphology commonly found in nature, as well as investigate the interdependence of active sensing and motor feedback - a topic which is just beginning to emerge in biological whisker research.

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- M. Fend, S. Bovet, and Pfeifer (in press). On the influence of morphology of tactile sensors for behavior and control. *Robotics and Autonomous Systems*

- H. Yokoi, M. Lungarella, M. Fend, and R. Pfeifer (2005). Artificial whiskers: structural characterization and implications for adaptive robots. *Journal of Robotics and Mechatronics*, 17(5) pages 584-595.

- M. Fend (2005), Whisker-based texture discrimination on a mobile robot, *Proceedings of the 8th European Conference on Artificial Life (ECAL), Kent, September 2005*, pages 302-311

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- V.V. Hafner, M. Fend, P. König, and K.P. Körding (2004), Predicting properties of the rat somatosensory system by sparse coding , *Neural Information Processing Letters and Reviews*, 4(1), pages 11-18, ISBN 89-89453-04-6 93560

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